Personalized Adaptive Endurance Training with Exergames

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Personalized Adaptive Endurance Training with Exergames

Personalisiertes, adaptives Ausdauertraining mit Exergames
Zur Erlangung des Grades eines Doktors der Naturwissenschaften (Dr. rer. nat.) genehmigte Dissertation im Fachbereich Humanwissenschaften von Katrin Hoffmann aus Reinheim
Tag der Einreichung: 28. August 2020, Tag der Prüfung: 29. Oktober 2020

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TECHNISCHE UNIVERSITÄT DARMSTADT

Human Sciences Department
Institute of Sport Science

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Erklärung zur Dissertation

Ich versichere hiermit, dass ich die Arbeit selbstständig verfasst, keine anderen, als die angegebenen Hilfsmittel verwendet und die Stellen, die anderen Werken im Wortlaut oder dem Sinne nach entnommen sind, mit Quellenangaben kenntlich gemacht habe.

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Abstract

Exergames, as part of “Serious Games”, have the potential to increase the amount of physical activity by using motivational computer game elements. This is particularly relevant for health sports since a regular and sustainable aerobic endurance training evokes a variety of health promoting effects. However, for Exergames to be deployed as efficient and effective training tools, it is essential to evoke and control individual strain corresponding to predefined training goals. In this context, the prediction of individual responses is essential for a fast and valid control of training.

Inspired by a prototypical Exergame, this thesis presents five studies analyzing how aerobic endurance training based on heart rate responses can be integrated into Exergames. This includes on one hand the analysis of individual heart rate responses to the change of load and possible influencing factors modulating these responses. On the other hand, this also included the development of algorithms for individual and adaptive strain control integrating the obtained insights and knowledge from previous research.

The first two studies present the development, optimization and evaluation process of a first evocation and control algorithm. Based on literature research and analyzes of heart rate responses to the change of load prior to training, an individual strain control is implemented.

In two further studies, individual factors possibly influencing these responses are analyzed regarding their predictive potential. The results indicate that relatively stable parameters (e.g., age, gender, etc.) are not suitable to be used as valid prediction parameters. Thus, identical load can lead to different responses in the same participant. In contrast, variable short-term factors (e.g., mood, physical health, time of day, etc.) have a strong influence on the individual heart rate responses. Individual strain responses can vary even within short training sessions. An online prediction based on heart rate responses during training seems to have the highest potential for a valid prediction.

In the last study, individual responses to the change of load are predicted using a mono-exponential equation. For this, only currently measured heart rate responses are analyzed and the final responses are incrementally calculated. The developed approach shows a satisfactory predictive potential.

The main contribution of this thesis is the identification of relevant aspects for the integration of an individual optimal strain control within Exergames for aerobic endurance training. These results stimulate further interdisciplinary research on studies from sport science and informatics to develop effective and efficient Exergames used as training tools in health sports.

Zusammenfassung

Exergames haben als „Serious Games“ das Potential, durch die Nutzung motivierender Computerspielelemente zu einer Erhöhung der allgemeinen körperlichen Aktivität beizutragen. Dies ist besonders im Gesundheitssport relevant, da ein regelmäßiges und kontrolliertes Training der allgemeinen aeroben Ausdauer eine Vielzahl an gesundheitsförderlichen Effekten hervorruft. Damit diese Computerspiele jedoch als effiziente und effektive Trainingsmittel genutzt werden können, muss eine zuverlässige Belastungs- und Beanspruchungskontrolle integriert werden. Insbesondere die Vorhersage individueller Reaktionen ist für eine schnelle und zuverlässige Trainingskontrolle entscheidend.

Inspiriert durch ein prototypisches Exergame stellt diese Thesis fünf Studien vor, wie ein herzfrequenzgesteuertes Training in Exergames für aerobes Ausdauertraining integriert werden kann. Dafür werden einerseits individuelle Herzfrequenzreaktionen auf Belastungsänderungen sowie mögliche Einflussfaktoren auf die Ausprägung dieser Reaktionen analysiert. Weiterhin werden aus bisheriger Forschung und den daraus gewonnenen Erkenntnissen Algorithmen für eine individuelle und adaptive Beanspruchungskontrolle und -vorhersage (weiter-)entwickelt.

In den ersten beiden Studien wird der Entwicklungs-, Optimierungs- und Evaluationsprozess eines ersten Ansteuerungs- und Kontrollalgorithmus vorgestellt. Basierend auf Literaturrecherchen und der Analyse individueller Herzfrequenzreaktionen auf Belastungsänderungen wird eine adaptive Beanspruchungskontrolle ermöglicht.

In zwei weiteren Studien werden individuelle Einflussflussfaktoren dieser Reaktionen auf ihr Vorhersage-Potential analysiert. Dabei wird gezeigt, dass bisher genutzte, langfristig gleichbleibende Parameter wie z. B. Alter, Geschlecht, etc. nicht geeignet sind, individuelle Herzfrequenzreaktionen zuverlässig vorherzusagen. So können identische Belastungen bei gleichen Probanden unterschiedliche Reaktionen hervorrufen. Dabei scheinen kurzfristig variable Parameter, wie z. B. Stimmung, körperliche Gesundheit oder Tageszeit einen starken Einfluss zu haben. Es wird gezeigt, dass sich individuelle Beanspruchungserscheinungen bereits innerhalb kurzer Trainingseinheiten ändern können. Eine Vorhersage anhand akut gemessener Herzfrequenzen während des Trainings scheint dabei das höchste Vorhersagepotential zu haben.

In der letzten Studie werden die individuellen Reaktionen auf Belastungsänderungen mit Hilfe einer exponentiellen Formel vorhergesagt. Dafür werden lediglich die akut gemessenen Herzfrequenzreaktionen analysiert und die individuellen Herzfrequenzreaktionen inkrementell berechnet. Die vorgestellte Methode lieferte für die meisten Herzfrequenzanstiege zufriedenstellende Ergebnisse. Insbesondere Herzfrequenzkurven mit flachen Anstieg wurden nicht mit ausreichender Qualität und Geschwindigkeit vorhergesagt. Der entwickelte Ansatz zeigt ein zufriedenstellendes Vorhersagepotential.

Der Hauptbeitrag dieser Thesis ist die Identifikation von relevanten Aspekten für die Integration einer individuell optimalen Beanspruchungskontrolle in Exergames für aerobes Ausdauertraining. Die Ergebnisse regen zukünftige, interdisziplinäre Forschung zu Experimenten aus Sportwissenschaft und Informatik an, um effektive und effiziente Exergames als Trainingsmittel für den Gesundheitssport zu entwickeln.

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List of Abbreviations

ΔHR ... *deviation of target heart rate and measured heart rate*
ΔHR_1 ... *Deviation of heart rate responses at the end of the first load level in calibration and exercise phase*
ΔHR_2 ... *Deviation of heart rate responses at the end of the second load level in calibration and exercise phase*
ACSM ... *American College of Sports Medicine*
ALC ... *Automatic Load Control*
ANS ... *autonomous nervous system*
BMI ... *Body Mass Index*
$c_{average}$ ... *value c (slope of HR response) averaged over all participants*
ECG ... *electro cardio gram*
ECM ... *extensive contiuous method*
EIM ... *extensive interval method*
FiF ... *Forum for Interdisziplinäre Forschung at Technical University of Darmstadt*
GEQ ... *Game Experience Questionnaire*
HIIT ... *high intensive interval training*
HMent ... *mental health*
HPhys ... *physical health*
HR ... *heart rate*
HR_1 ... *heart rate at timepoint 1*
HR_{1_calib} ... *mean heart rate in the last 30 sec of first load level (calibration phase)*
HR_{1_exer} ... *mean heart rate in the last 30 sec of first load level (exercise phase)*
HR_2 ... *heart rate at timepoint 2*
HR_{2_calib} ... *mean heart rate in the last 30 sec of second load level (calibration phase)*
HR_{2_exer} ... *mean heart rate in the last 30 sec of second load level (exercise phase)*
HR_{30} ... *heart rate 30 sec after onset of exercise*
HR_{level1} ... *steady state heart rate measured in first load level, evoked by P_{level1}*
HR_{level2} ... *steady state heart rate measured in second load level, evoked by P_{level2}*
HR_{max} ... *maximum heart rate measured during exhaustion test*
$HR_{max\_training}$ ... *maximum heart rate measured during training session*
HR_{real} ... *measured heart rate at defined timepoints*
HR_{start} ... *heart rate at the onset of load*
HR_{steady} ... *steady state heart rate*
HR_{steady_calc} ... *predicted steady state heart rate*
$HR_{training}$ ... *calculated individual optimal training heart rate*
$HR_{trainingScope}$ ... *individual optimal training heart rate range*
HRV ... *heart rate variability*
HSoc ... *social health*
ICM ... *intensive contiuous method*
IIM ... *intensive interval method*
Interf ... *interference caused by previous activity*
Interv ... *interval*
kids-geq ... *Game Experience Questionnaire adjusted for children*
KOM ... *Multimedia Communication Laboratory at Technical University of Darmstadt*
LA_{max} ... *maximum lactate level*
Nutr ... *nutrition*
O_2-dept ... *oxygen deficiency*
P ... *Power/ Load*
P_{1_sub} ... *calculated load applied at the ergometer expected to evoke responses below VT_1*
P_{2_sub} ... *calculated load applied at the ergometer expected to evoke responses between VT_1 and VT_2)*
P_{3_sub} ... *calculated load applied at the ergometer expected to evoke responses above VT_2)*

PA .... *physical activity*
PAL .... *physical activity level*
P_{level1} .... *load in first load level - required for calculating* P_{target}
P_{level1_calib} .... P_{level1} *in calibration phase*
P_{level1_exer} .... P_{level1} *in exercise phase*
P_{level2} .... *load in second load level - required for calculating* P_{target}
P_{level2_calib} .... P_{level2} *in calibration phase*
P_{level2_exer} .... P_{level2} *in exercise phase*
P_{max} .... *maximum load measured in the exhaustion test*
PR .... *pedal rate*
P_{target} .... *preprocessed target Load applied at the ergometer*
$P_{target\_estimated}$ .... *calculated target load, expected to evoke* $HR_{training}$
RM .... *repitition method*
SBS- .... *negative mood*
SBS+ .... *positive mood*
SV .... *stroke volume*
t_{30} .... *time point: 30 sec after onset of exercise*
t_{5bpm} .... *time point when the deviation of* HR_{steady_calc} *and* HR_{steady} *was smaller than 5 bpm*
t_{steady} .... *time point when* HR_{steady} *was reached*
VCM .... *varying contiuous method*
VCO_2 .... *amount of carbon dioxide removal*
VO_2 .... *amount of oxygen uptake*
VO_{2max} .... *maximum oxygen uptake*
VT_1 .... *first ventilatory threshold*
VT_2 .... *second ventilatory threshold*
WHO .... *World Health Organization*

1. Introduction and Motivation

All over the world, an increase of physical inactivity can be noticed in many countries (World Health Organisation - WHO, 2007; Guthold, Stevens, Riley, & Bull, 2018). This happens although several studies have already proven the positive relationship between physical activity (PA) and health (e.g., American College of Sports Medicine - ACSM, 2011; Pfeifer, 2005; Schlicht & Brand, 2007; WHO, 2010). Particularly, a well-developed aerobic endurance performance is an indispensable basis for the functionality of the human organism. Thus, a variety of studies verified that sustainable and regular aerobic endurance training increases the functionality of various organ systems. These include the cardiovascular system (e.g., Blomqvist & Saltin, 1983; Cornelissen & Fagard, 2005; Cornelissen & Smart, 2013; Kissel, Gabus, & Baggish, 2019), the respiratory system (e.g., Wasserman, Whipp, Koyl, & Beaver, 1973), the vascular system (e.g., Spengler, Roos, Laube, & Boutellier, 1999; Urhausen, Gabriel, & Kindermann, 1995), the immune system (e.g., Shephard, Rhind, & Shek, 1994; Simpson et al. 2012), and the brain (e.g., Chaouloff, 1989; Steiner, Murphy, McClellan, Carmichael, & Davis, 2011). Furthermore, the mortality risk, the risks of diseases such as coronary heart disease (Valkeinen, Aaltonen, Kujala, 2010), diabetes mellitus type 2 (e.g., Henriksen, 2002; Soukup, & Kovaleski, 1993), cancer (Shephard, 1993), or lifestyle diseases (e.g., back pain, anxiety states or depression; Teychenne, Ball, & Salmon, 2008; WHO, 2007) can be reduced.

Professional organizations and governmental agencies provide detailed information and recommendations to achieve these positive effects (e.g., WHO, 2010; ACSM, 2011). According to these guidelines, adults should accumulate at least 150 min of moderate-intensity activity or 75 min of vigorous-intensity activities per week. However, the required increase of calories burned to meet these recommendations is very challenging and hard to fulfill. The reasons for this are diverse. In addition to external barriers (e.g, lack of time, financial and social resources), a variety of internal barriers (e.g., lack of motivation) can occur (Denk & Pache, 1999, quoted from Schlicht & Brand, 2007, S. 48).

A promising approach to overcome potential motivational barriers is provided by “Serious Games”. Stated to be “More than Fun” (Göbel, Hardy, & Wendel, 2010), Serious Games aim to provide an entertaining and motivating experience while at the same time achieving a serious goal. In sport science, especially Exergames or Games for Health that are developed to increase the individual PA level have risen increased attention. In Exergames, (whole-) body movements of the player are measured using sensor technology and used for game control (Oh & Yang, 2010). Several studies proved a substantial motivating effect enhancing PA, at least at low levels (Peng, Lin, & Crouse, 2011; Wiemeyer & Kliem, 2012).

Since the commercial success of stationary game consoles (e.g., Wii Fit®, X Box Kinect®), the popularity, prominence, and use of Exergames has greatly increased. The advancing progress of technology has increased usability and performance, so that nowadays Exergames are even integrated into everyday devices such as smartphones (Mukhopadhyay, 2015).

A big advantage of Exergames is the integration of measured parameters necessary for training control. The immediate and computerized analysis of individual responses enables an objective and fast control of these parameters. This allows Exergames to be used as efficient and effective training resources without overstraining or underchallenging the training person. Advanced sensor technology (e.g., wearables) and improved processing algorithms (e.g., artificial intelligence) allows for improved reliability and usability of the measured and controlled parameters. Additionally, balancing task difficulty and skill level also increases the motivation and the adherence to the game (Sinclair, Hingston, Masek, & Nosaka, 2010).

Up to date, Exergames have been focused by numerous research projects. However, most studies focus on the motivational potential or increase of PA of Exergames. A control of intensity of PA particularly in aerobic endurance training is only occasionally and unsatisfyingly provided in either console or smartphone games (Althoff, White, & Horvitz, 2016, Whitehead, Johnston, Nixon, & Welch, 2010). A control of strain based on the insights from training science can be found even more rarely. However, this lack of suitable concepts contradicts the demand for increased individualization and personalization of Exergames (Hardy, Dutz, Wiemeyer, Göbel, & Steinmetz, 2015). Therefore, there is an urgent need for research in the field of individualized strain control within Exergames for aerobic endurance training.

This particularly accounts for the use of Exergames in health sport. In general, only little knowledge about the individual responses to applied stress is available for the participants in this context. Neither training plans nor the responses to previous trainings can be analyzed. Nevertheless, approaches for strain control integrated in Exergames need to be accurate despite the lack of information. It is essential to validly measure, model and predict the varying individual responses of the participants. Considering these aspects, Exergames have the potential to enable an efficient and effective strain control with at least information possible and as fast as possible.

Although a large number of input devices for controlling Exergames are currently available, especially the use of a bike ergometer has clear advantages. The risk of injuries is reduced due to the limited (bio-)mechanical degrees of freedom and the weight support of the participant. The ergometer allows for precise load control as well as high reliability and validity of data.

The aim of this thesis is the implementation and improvement of strain control inside Exergames for endurance training controlled by a bike ergometer. In this thesis, HR was chosen as parameter representing individual strain. As shown in Figure 1.1, three related aspects are crucial:

The approaches for controlling and predicting strain in Exergames aim to evoke predefined individual responses. These individual responses must in turn be analyzed and integrated in order to ensure a valid control. Furthermore, the responses are influenced by internal and external factors that need to be integrated correspondingly.

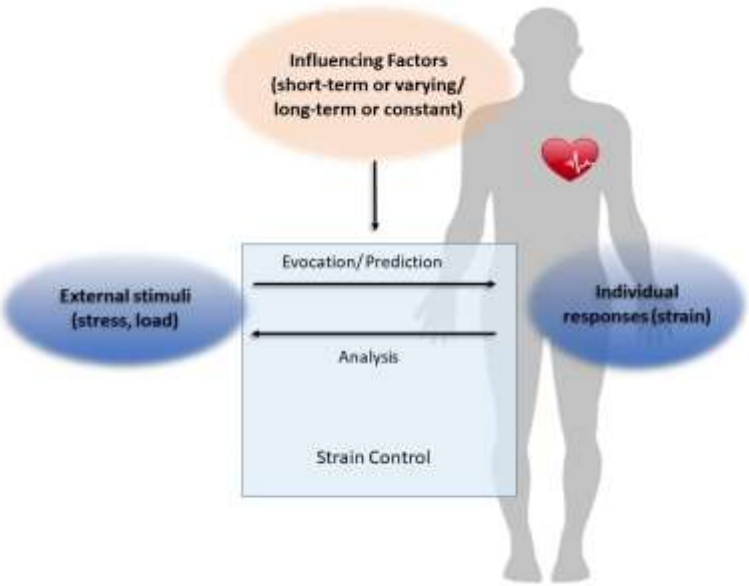

Figure 1.1 Controlling scheme for strain control in endurance training.

In this context, this thesis focuses on the following three aspects:

1. Extension of knowledge about HR responses to the change of load bouts within a physical training by analysis of individual responses.
2. Identification of relevant influencing factors that are essential for a valid HR prediction.
3. Development and analysis of different approaches for control and prediction of HR in Exergames.

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2. Theoretical Background

In order to use Exergames as effective and efficient training tools, it is important to understand the basic principles of human responses to applied stress. The following chapter presents essential information from training science and physiology.

2.1. Stress – strain – responses to Training

In general, physical training is defined as the methodical, sustainable and purposeful performance of exercises or motion sequences (de Marées & Mester, 1981, 175). These external stimuli or influences (*stress or load*, e.g., power, speed, etc.) evoke individual responses (*strain)* in various organ systems of the human body. This process aims to apply individually optimal strain onto the human body. The goal is to evoke sustained functional and morphological responses of the stressed systems corresponding to predefined training goals (Weineck, 2019, 22f; see figure 2.1). Therefore, an individualized and adaptive stress control enables a personalized training. Please note that "Adaptation" is referring to the genetically acquired or physiologically responsive adjustment of organisms to environmental stimuli. In this thesis, the term adaptation is used for long lasting or chronic responses in the physical training process.

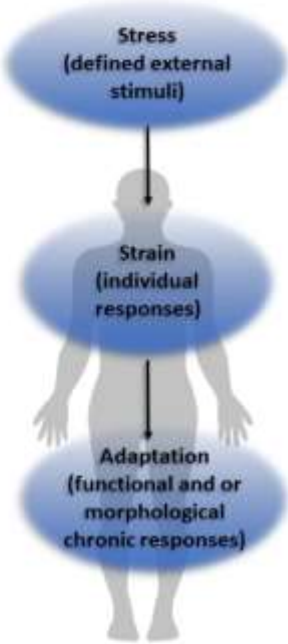

Figure 2.1 Stress - strain - adaptation

A fast and controlled evoking of individual strain is important to neither overstrain nor underchallenge the training person. Overstraining might lead to risks like injuries, diseases or to termination of training. Underchallenging leads to an inefficient or ineffective training.

However, finding optimal stress evoking individually optimal strain corresponding to the training goals is not trivial. Particularly in aerobic endurance training, the complex nesting and interconnection of different organ systems (e.g., cardiovascular system, respiratory system, metabolic system, endocrine system, and nervous system), the dependency on different prerequisites, training conditions and highly varying influencing factors of each system (Antoni, 1989, Esperer, 2004) must be considered. Due to these varying conditions, identical workload can lead to varying responses in different individuals.

2.2. Measuring strain via heart rate – heart rate as biological signal

The knowledge about the complex interaction of different organ systems is essential for a valid determination of individual strain in endurance training. Although it is possible to measure the responses of each system separately, measurement of most indicators can only be performed with laboratory equipment or under resting conditions. Measurement of human metabolism using direct or indirect calorimetry requires reliable, valid and very sensitive gas analyzers that measure the amount of oxygen uptake (VO_2) and carbon dioxide removal (VCO_2). Additionally, this expensive device mostly requires a complex calibration routine prior to the measurement and is therefore not suitable for spontaneous and immediate use (Macfarlane, 2017). Many indicators for muscle metabolism or the endocrine system require invasive procedures and a laboratory equipment to analyze the blood, urine or saliva samples (Ferrari, Binzoni, & Quaresima, 1997; Vining, & McGinley, 1987). Therefore, the described measuring procedures are not suitable to be used in a training process performed in the desired context.

However, particularly the cardiovascular system plays an important role in the complex interaction of these systems. It is responsible for supplying all cells of the human organism with oxygen and nutrients, removal of carbon dioxide and metabolites, and it works as a transport system for substances dissolved in blood, e.g., hormones, vitamins, and enzymes (Weiss & Jelkmann, 1989; Ulmer, 1989). The human heart works as the pump that drives the blood through the human body. Its performance is therefore assumed to be a good indicator representing the individual strain of the whole body.

The performance of heart (*Cardiac Output*) depends on the frequency of heart cycle (*heart rate - HR*) and amount of blood ejected (*stroke volume – SV*) following (De Marées & Mester, 1981; Esperer, 2004):

– **Equation 2.1:** ***Cardiac output = HR * SV.***

However, measuring cardiac output is not trivial. Due to the central location of the heart inside the torso and the vulnerability of the cardiorespiratory system, a direct measurement of the heart function is very difficult. Furthermore, measuring SV is difficult as a clinical setting or a non-moving patient is required (i.e. use of catheter in echocardiography, direct Fick method). Therefore, the heart function is measured indirectly by signals that are caused by these functions. In the desired context, HR or effects inside the human body that are caused by the heartbeat seem to be promising. The most commonly used sensors measure the changes in energy potentials that are caused by the spread of excitation during the heart cycle. These electrographic sensors (i.e. electrocardiogram, HR breast belts) show a high reliability and low susceptibility to external error sources (Weippert, Kumar, Kreuzfeld, Arndt, Rieger, & Stoll, 2010). Additionally, the pulse wave conducting through the human body can be measured using optical sensors, sensors monitoring magnetic induction, infrasonic cardiac vibration sensors and sphygmographic sensors. Furthermore, heart murmurs can be measured by phonocardiographic sensors. Compared to electrographic measurements, all listed sensor technologies still either lack reliability or show high interferences caused by external influences or motion artefacts (Teichmann et al., 2012; Selvaraj, Jaryal, Santhosh, Deepak, & Anand, 2008; Kugler, Rollnik, & Schmitz, 1997).

2.3. Characteristics of heart rate responses

The modulation of HR is realized by the integration of the human heart into a multitude of complex regulatory mechanisms and reflexes that respond to afferences from sensors located throughout the human body (Malik, 1996; Guttermann, 1996). These modulations are the basis for a fast and effective adjustment of blood flow corresponding to the requirements and for the protection of the human organism (e.g., against harmful fluctuations of blood pressure or volume). Additionally, a variety of internal and external influencing factors modulates the adjustment of the heart performance. Depending on the time elapsed to modulate the HR response, different kinetics can be distinguished:

- Ultra-short term modulation
- Short-term or acute responses
- Mid-term responses
- Long-term or chronic responses

„*Ultra-short term modulation*" is mainly caused by the strong modulating effect of the autonomous nervous system (ANS). By recording every single heartbeat, a high variation of longer and shorter lasting heart cycles can be observed (see Figure 2.2). This variance is called heart rate variability (*HRV*, Werdan, Schmidt, Hennen, & Müller-Werdan, 2005). HRV represents the end-organ response to the complex integration into regulatory mechanisms and reflexes (e.g., Frank-Starling Law, arterial baroreflexes, respiratory sinus-arrhythmia; Malik, 1996; Guttermann, 1996). The assumption that the activity of these mechanisms and reflexes can be detected using spectral analysis of HRV is strongly doubted and highly debated in recent literature (Monfredi et al. 2014, Picard Tan, Zafonte, & Taylor, 2009). The HRV is pronounced at rest due to the dominance of the repressing parasympathetic activity and its beat to beat modulating potential. With increasing intensity, the stimulating sympathetic activity increases and HRV decreases.

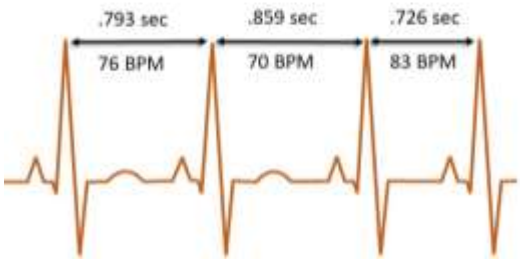

Figure 2.2 Prototypical representation of heart rate variability

„*Short-term or acute responses*" express the responses to the change of load on the human body. If load increases, the working muscles have an increased oxygen demand. Therefore, the partial pressure of oxygen decreases and partial pressure of carbon dioxide increases in the blood. Corresponding reflexes provoke the decrease of parasympathetic activation with concurring increased sympathetic activation. HR, SV, and VO_2 are increasing. Due to a slow signal transduction and transmitter metabolism of catecholamine, the sympathetic influence is delayed by 1 – 2 sec and reaches its maximum only after 30 – 60 sec. Therefore, the slopes of HR and VO_2 show a delayed response. After a linear increase independent of intensity, the HR slope follows an exponential increase (Bunc, Heller, & Leso, 1988). In submaximal range, HR and VO_2 level off into a steady state (Springer, Barstow, Wassermann, & Cooper, 1991; Ricardo, de Almeida, Franklin, & Araújo, 2005; see Figure 2.3). In maximal range, the accumulating lactate causes an acidosis of blood. Thus, a continuous rise of HR and VO_2 with no clear Steady State can be observed.

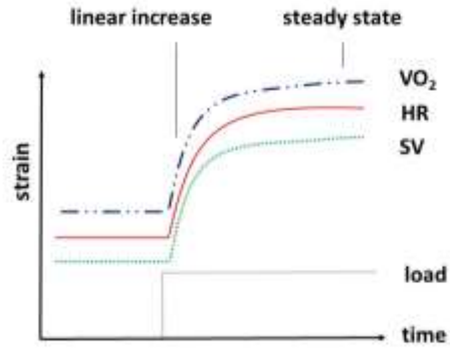

Figure 2.3 Prototypical acute responses of heart rate (HR), oxygen uptake (VO_2) and stroke volume (SV) to the change of submaximal load

Additionally, particularities may occasionally occur in participants:

- Cardiac drift
- Pre-start situation
- Decrease into steady state

A slow but continuous rise of HR can be observed in training sessions even in the submaximal range. This *cardiac drift* is accompanied by a decrease in SV and constant VO_2. The effect is particularly evident in long training sessions (Dawson et al., 2005; Jeukendrup & Van Diemen, 1998) but was also detected in short training sessions lasting up to 30 min (Wingo, LaFrenz, Ganio, Edwards, & Cureton, 2005). The underlying mechanisms are still unclear (Wingo et al., 2005). It is probably caused by a reduced diastolic function (Achten & Jeukendrup, 2003) or by hypovolemia and hyperthermia (Coyle & González-Alonso, 2001; see Figure 2.4).

The pre-start situation is characterized by an increase in HR and VO_2 without an actual increase of exercise intensity. At the onset of exercise, working cells are forced to use anaerobic alactacide energy supply due to the delayed sympathetic influence and therefore the insufficient supply with oxygen. This oxygen deficiency (O_2 debt) is usually compensated after exercise. The *pre-start situation* is possibly caused by anticipatory effects and reduces the effect of *O_2 debt* (Schmole, 1984; see Figure 2.4).

At low intensities, an overshooting response of HR and VO_2 with a successive *decrease into steady state* can occur. This response appeared during exhaustion tests within our studies. The described slope is potentially caused by an O_2-debt that is compensated already during exercise. Since this phenomenon occurs only sporadically and in isolated participants, only few studies are currently available (see Figure 2.5).

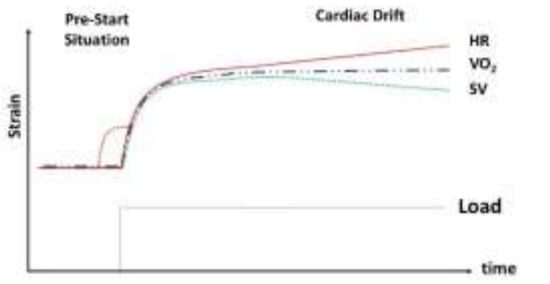

Figure 2.4 Prototypical representation of Pre-Start Situation and Cardiac Drift – HR: heart rate, VO_2: oxygen uptake, SV: stroke volume

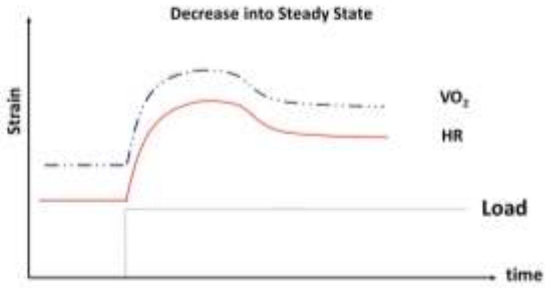

Figure 2.5 Prototypical representation of decrease into Steady State – HR: heart rate, VO_2: oxygen uptake

Due to the individuality of responses, all particularities are difficult to model or to predict during the physical training process. Therefore, the described particularities have been deliberately omitted in this thesis.

"Mid-term responses" are expressed by the relationship of stress intensity and corresponding responses of cardiopulmonary indicators. At low intensities, especially the HR response tends to be evaluated due to possible anticipatory effects. VO_2 also shows a linear but slower increase (Weineck, 2010, S. 53, Brooke & Hamley, 1972). In the submaximal range, the energy in the muscle cells is mainly supplied by aerobic metabolization. The increased demand of oxygen in the cells can be provided by an increased ventilation and heart performance. In this range, HR and VO_2 are linearly related to intensity (Vokac, Bell, Bautz-Holter, & Rodahl, 1975). If intensity is increasing, the energy requirements of the cells cannot be sufficiently covered by the aerobic energy supply. Beginning with the first ventilatory threshold (VT_1) a mixed energy supply with aerobic and anaerobic lactate metabolization is occurring. The metabolite lactate is released into the blood. However, this acidosis is sufficiently cached by the bicarbonate buffer and eliminated by respiratory compensation. Furthermore, lactate is transported to the metabolizing organs (e.g., liver, kidney, heart muscle) correspondingly. A lactate steady state occurs due to the increase of lactate elimination (Weineck, 2010). If the intensity increases even further, a second ventilatory threshold (VT_2) can be determined. At this point, an elevation of HR and VO_2 is not sufficient to supply the cells with oxygen. A deflection point of HR can be observed. Additionally, SV shows a varying response. A secondary increase, a leveling off and even a drop of SV can occur (Vella & Robergs, 2005). A disproportional respiratory compensation is recognizable. The acidosis can no longer be compensated by ventilation. VCO_2 increases significantly with possible intersection of the VO_2 slope. At maximum lactate levels (LA_{max}), the glycolytic metabolism decreases locally by enzyme inhibition due to self-protection against excessively low pH values. The maximum values (LA_{max}, maximum oxygen uptake - VO_{2max} and maximum heart rate - HR_{max}) are reached. The body can no longer increase its performance leading to a termination of exercise (Weineck, 2010; see Figure 2.6).

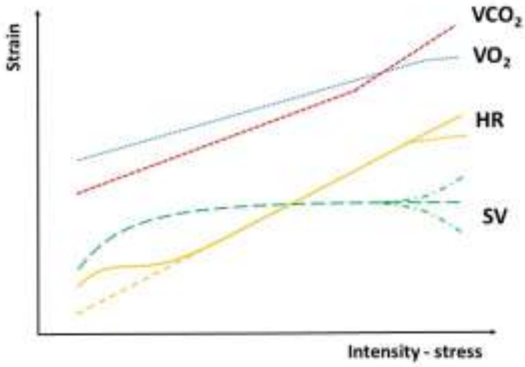

Figure 2.6 Prototypical representation of midterm responses (Pokan et al., 2004; Vella & Robergs, 2005) – HR: heart rate, VO_2: oxygen uptake, VCO_2: carbon dioxide removal, SV: stroke volume.

"Long-term or chronic responses" are functional and morphological changes and adjustments to prolonged training. In sport science and physiology, these responses are called "adaptation". These changes are, e.g., hypertrophy of the heart leading to a higher cardiac output with reduced resting and training HR or an increase of respiratory capacity (Weineck, 2019).

The following manuscripts concentrate mainly on modeling and predicting short-term dynamics representing the acute responses to the change of load bouts. To minimize influence of the particularities occurring in very low and high intensities, the modelled range is assumed to stay submaximal. In this range, a linear relationship of intensity and HR as well as a leveling off of HR into a steady state is reasonable (Weineck, 2019).

2.4. Endurance Training - Methods

After clarifying how the human organism responds to physical stress, the question arises how the adaptation processes should be structured to provide an effective and efficient endurance training.

In sports science literature, a variety of different training methods for endurance training is available. Depending on the training method, specific regulation processes are evoked which in turn cause load-specific adaptation processes in the respective systems (Schnabel, Harre, & Borde, 1997). A problem analyzing the literature is that training methods vary in their specifications depending on the author. Therefore, a clear demarcation of the individual methods is difficult. The following table (see Table 2.1) gives a summary of the current training methods including training parameters and primary adaptation.

However, not all listed training methods are feasible to be used in Exergames or in health sports. Special training methods that are used to develop performance-related requirements for competitions or competition methods should be avoided due to the potential overloading of individual systems or the whole organism (Schnabel, Harre, & Borde, 1997; WHO, 2010). Therefore, general training methods should be preferred.

For a reasonable use in Exergames, the chosen training methods should be as motivating as possible. Interval training, for example, is perceived as more motivating than continuous training. In particular, High intensity interval training (HIIT) has gained attention in recent years. Studies verified positive effects of HIIT on cardiometabolic health and motivation

(Ramos, Dalleck, Tjonna, Beetham, & Coombes, 2015; Kilpatrick, Jung & Little, 2014; Oliveira, Santos, Kilpatrick, Pires, & Deslandes, 2018). However, this training method should be used with caution due to the risk of injury or other adverse events.

In general, health-oriented endurance training should comprise a total volume of 75 min of intensive or 150 min extensive training with at least 3 training sessions per week (WHO, 2010).

Table 2.1 Summary of training methods for endurance training (Bös & Banzer, 2006, S. 245ff, Schnabel, Harre & Borde, 1997, S. 259ff; Weineck, 2019, Kilpatrick, Jung & Little, 2014) – HR_{max}: maximum heart rate.

Name	Intensity	Duration of stress	Break	Primary responses
Extensive Continuous Method (*ECM*)	45 – 70 % HR_{max} (moderate)	30 - 60 min	No break	Basic endurance, oxygen uptake, lipid metabolism, regeneration
Intensive Continuous Method (*ICM*)	70 – 95 % HR_{max} (moderate - high)	20 – 60 min	No break	Aerobic-anaerobic endurance, muscle metabolism, glycogen storage
Varying Continuous Method (*VCM*)	50 – 95% HR_{max} (varying)	20 – 60 min	No break	Aerobic-anaerobic transition, motivational effects
Extensive Interval Method (*EIM*)	60 – 85 % HR_{max} (moderate - high)	1 – 15 min	Incomplete/ rewarding 15 – 90 sec	Aerobic-anaerobic endurance, muscle metabolism, capillarization, cardio-vascular functionality
Intensive Interval Method (*IIM*)	80 - 100% HR_{max} (very high)	6 – 90 sec	Incomplete/ rewarding 15 sec – 4 min	Anaerobic endurance, cardio-vascular functionality
Repetition Method (*RM*)	90 – 100% HR_{max} (very high)	15 sec – 3 min	Complete recovery	Anaerobic endurance, lactate compensation, endothelial function
High Intensive Interval Method (*HIIT*)	100% (very high - supramaximal)	30 sec – 60 sec	Incomplete/ rewarding 60 sec – 4 min	Maximal oxygen uptake, muscle metabolism

2.5. References

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3. Overview

This dissertation contains five manuscripts presented in separate chapters.

All manuscripts have been published in journals and/or presented at conferences including a peer-review procedure. Information on each publisher and the original publication can be found at the chapter's cover page. Each manuscript contains a summary of the references. All abbreviations found in the manuscripts have been unified for improved readability. In case of identical labels for tables or figures (e.g., "demographic description"), the name of the paper has been added to the title. The content of all articles is summarized in the following paragraphs.

The thesis is grounded on an exploratory approach. Based on literature research, an algorithm for individual strain control applicable in Exergames was developed (Manuscript I and Manuscript II). During the validation, the high inter- and intra-individual variance of HR responses affected the effectiveness and efficiency of the algorithm. Thus, possible influencing factors were analyzed (Manuscript III and Manuscript IV) and a prediction algorithm based only on measured HR values was developed (Manuscript V). All manuscripts are integrated in the controlling scheme displayed in chapter 1 emphasizing the affiliation to the distinct aspects (see Figure 3.1). The flowchart of the research process and the relationship between different manuscripts are illustrated in Figure 3.2.

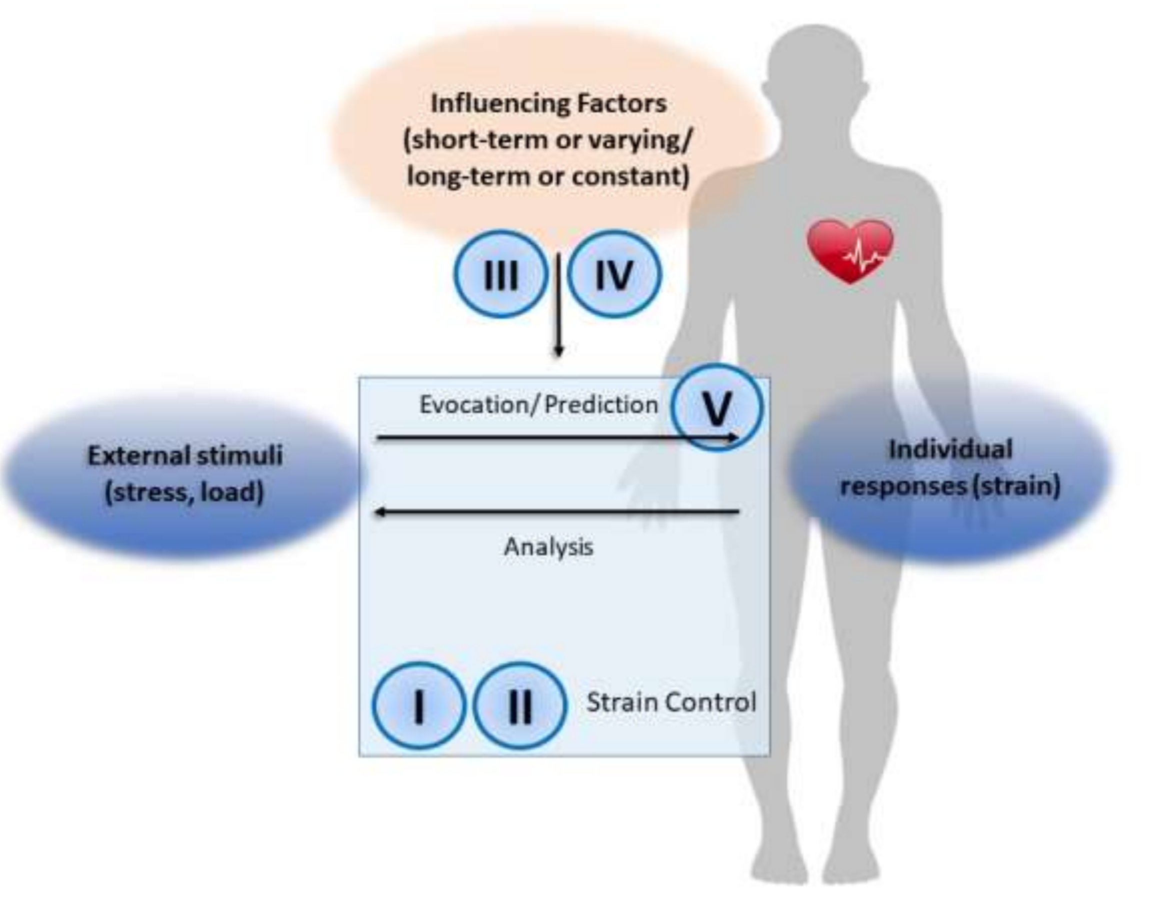

Figure 3.1 Controlling scheme for strain control in aerobic endurance training with integrated Manuscripts.

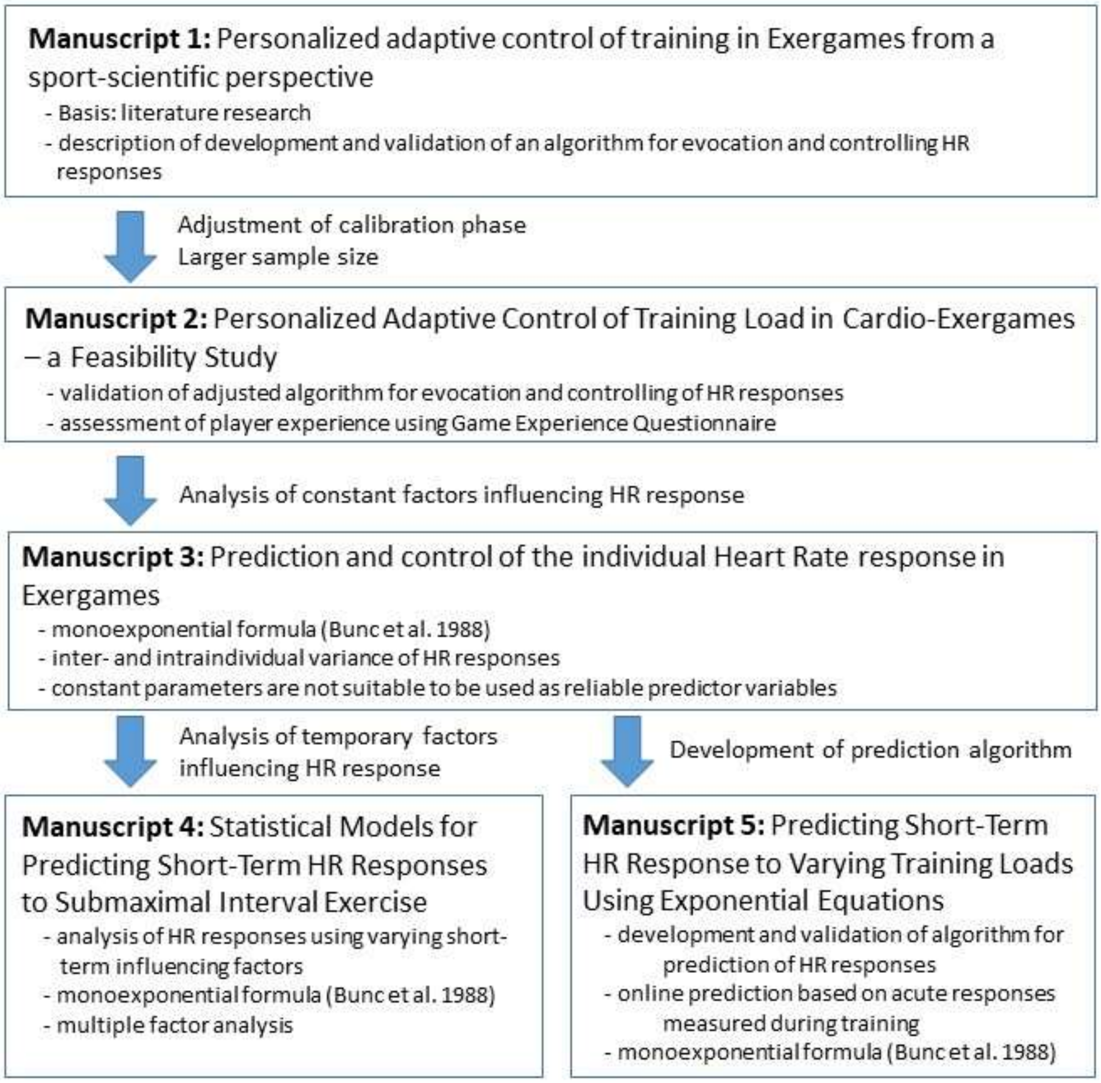

Figure 3.2 Flowchart research process and publications.

3.1. Manuscript I: Personalized adaptive control of training in Exergames from a sport-scientific perspective

Manuscript I addresses the first approach to evoke and control the individual training HR inside an Exergame for aerobic endurance training. Based mainly on literature search, an algorithm was developed that consisted of two parts. The first part used individual HR responses to linearly extrapolate a specific load that was expected to evoke a defined target HR. Thus, a calibration routine was applied prior to the training. Individual steady state HRs (HR_{steady}) to two defined load levels depending on the body mass index (BMI; BMI = weight [kg] / (height [kg])^2) of the participants were measured. An individual calculated target load (P_{target}) that was expected to evoke a pre-calculated individual optimal training HR ($HR_{training}$) was calculated using the measured data. The second part of the algorithm aimed at guiding the individual HR into a defined HR training zone ($HR_{trainingScope}$). Thus, the calibration phase was replicated and P_{target} successively set at the ergometer. Subsequently, load was automatically adjusted according to current HR values of the participant.

The Exergame "LetterBird" used in the study was developed by the communication laboratory (KOM) in Darmstadt. The Exergame was controlled using a bike ergometer by varying the pedal rate (PR). PR controlling the game was adjusted, so PR has a no significant influence on HR (Löllgen, Graham, & Sjogaard, 1980).

Although the approach was successful in guiding the individual HR into $HR_{trainingScope}$, the presented calculation for evocation proved to be not suitable for all participants. In the first study, overshooting HR responses were observed in two participants. These responses beyond $HR_{trainingScope}$ involve health risks particularly for the intended target group. Adjustments of the evocation part of the algorithm were necessary allowing for a slower but continuous increase of HR to $HR_{training}$. Possible efficiency issues were accepted in favor of avoiding overshooting responses.

Additionally, the calculation of mean HR values in the calibration routine was reduced to 30 sec preventing the unintentional integration of increasing HR data into calculation. Manuscript I shows that the adjusted version is a reasonable approach to ensure an individual and adaptive control of training inside an Exergame in the presented sample.

However, further weaknesses were revealed in the study. The classification of the participants for individualized determination of load in the calibration phase required improvements. Parameters that might influence the course of adaptation needed to be investigated, such as age, cycling experience and performance level (e.g., athletes versus non-athletes). Especially the cycling experience might be an important factor. In the study, especially participants with a low cycling experience showed a higher PR range than required to control the game. Either the influence of high oscillations on HR has to be integrated in the algorithm or the game mechanics has to ensure that PR stays within the expected range.

3.2. Manuscript II: Personalized Adaptive Control of Training Load in Cardio-Exergames – a Feasibility Study

The second chapter describes the investigation of the adjusted approach presented in Manuscript I in a larger sample. It was applied as a feasibility study to gather more information about individual stress responses of HR and to study the usability of the adjusted algorithm. Additionally, game experience while playing the applied Exergame was investigated.

Based on the findings of Manuscript I, the PA level was additionally included to improve determining the load levels of the calibration phase. Thus, the load applied in the calibration phase was set according to the BMI and PA level, respectively. The classification into active and non-active was established depending on the recommendations of the ACSM and WHO (ACSM 2011, WHO, 2019). The target load was reduced by 10% allowing HR to approach $HR_{trainingScope}$ from beneath. Game Experience was assessed using an adjusted version of the Game experience questionnaire (GEQ). The adjusted version of the GEQ uses a child-friendly format and wording while covering all relevant aspects of game experience (i.e. flow, challenge, competence, tension, negative affect, positive affect, and immersion; Poels, IJsselsteijn, & de Kort, 2008).

Results showed a very individual and varying HR response in the participants. Interestingly, even the HR response to the same change of load was varying in some participants. Although the mean values were not significantly different from zero, a substantial deviation was observed in two participants. The individuality of HandersR responses was also evident in the further course of training. Shortly after applying P_{target}, some participants already showed an increased HR response beyond $HR_{training}$ even though the load was specifically reduced to prevent this increase. Additionally, a high amount of load adjustment to maintain HR within $HR_{trainingScope}$ was necessary in 13 of 16 participants. Due to an unduly long overpassing HR response of one participant, the period for automatic adjustment of load was reduced to 30 sec during the study. Unfortunately, the technical implementation of the game allows an adjustment of load only at defined time points. The load was not adjusted to HR responses within this period. This fixed period proved to be not suitable for an individualized adjustment. A variable enquiry, depending on overshooting or falling below the target zone, might accelerate the HR control and prevent possible HR influences performed by the participants using breathing techniques.

Despite the high variety of responses, the results demonstrated a satisfying evocation and maintenance of $HR_{training}$ using the adjusted algorithm. After 10 min, only one participant showed a slightly increased response of 0.6 % above $HR_{trainingScope}$. Recommendations to classify the participants for an improved application of the load levels in the calibration phase based on the current sample were presented. Analysis of GEQ revealed the motivational effect of the applied Exergame. However, long-term effects still need to be investigated.

Although the evocation of a $HR_{training}$ is feasible using the presented algorithms, the authors assumed that an integration of the slope of the HR response is essential to improve HR control.

Therefore, Manuscript III, IV and V investigate the usability of a monoexponential formula for modeling and predicting the slope and corresponding steady state HR to the change of submaximal load.

3.3. Manuscript III: Prediction and control of the individual Heart Rate response in Exergames

Manuscript III describes the investigation to what extend individual parameters can be used to predict individual HR responses. Therefore, individual HR responses were modeled by a mono exponential formula (Bunc et al. 1988). Well established factors (e.g., age, gender, body weight, and training status) influencing the HR response were analyzed. Based on the data obtained in Manuscript II, we investigated if the slope of the HR course reveals individual or group specific patterns.

In the literature, a variety of formulas and procedures are available describing and modeling HR responses to the change of load (Ludwig, Sunduram, Füller, Asteroth, & Prassler, 2015; Ludwig, Hoffmann, Endler, Asteroth, & Wiemeyer, 2018). To provide an approach based only on actual HR values, the mono exponential formula developed by Bunc, Heller, and Leso (1988) was used. This formula models HR responses taking into account only the HR at the onset of load (HR_{start}), steady state HR induced by the corresponding load (HR_{steady}), HR values obtained during training and the slope of the course represented by value c:

- **Equation 3.1:** $\boldsymbol{HR = HR_{steady} - \left(HR_{steady} - HR_{start}\right) * e^{-c*t}}$

A first study proved the usability and representation of HR data with sufficient precision (r^2 = 0.86, SD = 0.13, $Range$ = 0.21; Hoffmann, Wiemeyer, Hardy, & Göbel, 2014). Bunc et al. (1988) already proved the significant influence of fitness level (trained versus untrained) on the changes of HR response. They assumed that trained individuals show a faster and lower HR response compared to non-athletes stressed with the same intensity. This assumption is supported taking into account the increased heart performance and a faster response of the ANS in athletes caused by the functional and morphological adaptations during the training process. Thus, Bunc et al. (1988) show a dependency between age, gender, and body weight and the slope of the response course.

In our sample, we could not confirm the influence on the HR response described in literature. All correlations between c and either body weight, age, and activity level were inconsistent and small in all load conditions. Only one exception occurred at one distinct load level. Furthermore, no invariant individual patterns were found in the responses. This emphasizes the findings from Manuscript II where varying responses in HR_{steady} were observed in particular participants. The course of the HR response was also varying even with identical change of load in the same individual. A differential influence of gender on value c depending on the load was revealed.

This leads to the conclusion, that the described influencing factors are not suitable to be used as valid predictors for HR responses to the change of load. Only gender differences can be considered depending on intensity of the applied load.

As these rather constant parameters do not provide a valid prediction, we assume the presence of rather temporal influencing factors. This assumption can exemplarily be confirmed by analysis of PR. While playing, a higher cadence was observed than required to control the game. An increase of PR beyond 100 RPMs significantly influences HR (Löllgen et al., 1980). Another way to predict individual responses is by calculating the slope of the response based on current HR values already during the process of HR adjustment to the change of load bouts. Manuscripts IV and V investigate the predictive potential of these two different approaches.

3.4. Manuscript IV: Statistical Models for Predicting Short-Term HR Responses to Submaximal Interval Exercise

As described in Manuscript III, a varying response to the change of identical load bouts can be observed in the same individual. This chapter describes the investigation of possible varying and transient influencing factors on HR responses.

Therefore, individual responses during a twelve-week training study were analyzed to expand the amount of analyzed data. Different training protocols were applied during the training process. Intensities of each protocol were set corresponding to individual responses obtained in testing procedures prior to and during the training in week 4 and week 8. Load was individually estimated to evoke similar HR responses throughout the training process. The analysis of HR responses during the extensive interval protocol allowed for analyzing five successive HR adaptation courses to submaximal load levels of each training. To increase the validity and comparability of data, this study was conducted without an Exergame. Thus, potential influences of exceeding PR or motivational gameplay on HR were excluded.

High individual day-to-day HR variations, as well as increases of HR_{start} and HR_{steady} during the training sessions were found with no dependency of training week. The obtained HR variations were therefore mainly depending on short-term influencing factors.

The influence of single psychophysiological states on individual HR responses was already revealed in a variety of studies (Brosschot & Thayer, 2003; Ewing, Neilson, Shapiro, Stewart,

& Reid, 1991; Heseltine, Potter, Hartley, Macdonald, & James, 1990). During a longer training process, it is challenging to control all described factors and investigate the influence of single parameters. In the presented study, a selection of relevant parameters was assessed prior to the training sessions with suitable questionnaires (i.e. type, duration and intensity of sports activity, nutrition, restfulness of sleep, aspects of mood, or health status). A multiple factor analysis of these parameters was performed.

As a result, individual and general influencing factors especially on HR_{start} and HR_{steady} were revealed. The number of intervals, physical health, Time of the day and negative mood were identified as important short-term factors influencing HR responses. However, only weak predictors for the slope of HR were identified. Therefore, further factors seem to influence the slope that were not sufficiently covered in the study. Further investigations are necessary extending the identified parameters (e.g., climate, temperature, drinking behavior during training).

3.5. Manuscript V: Predicting Short-Term HR Response to Varying Training Loads Using Exponential Equations

Another approach to predict individual HR responses is to analyze acute responses online during the change of load bouts. Manuscript V analyzes the prediction potential of an algorithm based on the formula presented by Bunc et al. (1988). The developed algorithm only processes individual HR values and the increase of response during the change of load bouts. Individual HR_{steady} corresponding to the applied load are incrementally calculated without any information about the level of load change. Using the HR data of the study presented in Manuscript IV, the reliability of this approach is analyzed. Additionally, a detailed analysis of the obtained HR data is presented.

The developed approach shows satisfying predictive potential. As expected, the prediction precision increased during the calculation process. Already after 60 sec, HR_{steady} was correctly predicted in 81% of all courses in three of four participants, but only in 32% in participant 4. After 90 sec, 80% of all courses were correctly predicted.

The presented analysis leaves some open questions. Especially signal processing of the individual HR values was challenging due to the heart rate variability. It is not trivial to find a compromise between precision of HR data and noise reduction essential for prediction. Therefore, the preprocessing of HR values needs to be improved to increase prediction quality. One possibility is to identify further time points or plateaus recognizable during the slope of the HR course, e.g., when HR courses changes from linear to exponential increase. Additionally, the predictive quality of further formulas needs to be investigated. Thus, insight are gained if more parameters are essential for a more valid and faster prediction.

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4. Manuscript I: Personalized adaptive control of training load in Exergames from a sport-scientific perspective

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Katrin Hoffmann is the main and corresponding author of this article responsible for the conception and design of the study and writing of the manuscript. Josef Wiemeyer was the supervisor of the project and contributed in discussions regarding interpretation of the results and writing the paper.
Sandro Hardy was responsible for the development of the applied Exergames LetterBird and contributed information regarding the game design. Stefan Göbel was the supervisor of the development of the applied Exergame.

4.1. Abstract

The following paper addresses the development and first tests of an algorithm for individual control of physical load in Serious Games for Sports and Health. The purpose is to monitor and control the heart rate (HR) as an individual indicator of optimal training load. In the context of the Serious Game “LetterBird”, developed by KOM, a playful and yet effective physical training can be realized. In this game the flight of a pidgeon is controlled by a cycle ergometer. The goal is to collect letters approaching the bird at different altitudes.

From the perspective of computer science in sport, the aim was to generate an algorithm that approaches and maintains a defined target HR effectively and efficiently in individuals with different properties (e.g., age, sex, performance and health level) within the game.

For an initial application and testing of this algorithm, a two-part test series was performed with 4 participants. The results are promising: The intended HR could be evoked in all participants. Yet further tests need to be done to improve the adaptations.

4.2. Introduction

The current socio-demographic situation in many countries is characterized by a high prevalence of physical inactivity as one major risk factor for mortality (ACSM, 2011; WHO, 2010). Therefore, many professional organizations and governmental agencies call for more physical activity (PA), particularly aerobic training. Nevertheless, the recommendations of these organizations to increase the number of burned calories per week are very challenging and hard to fulfill. Hence, motivational issues are a serious barrier to increasing PA.

Serious Games offer a possible option to solve this problem because these games claim to exploit the engaging and motivating effects of computer games to reach serious goals. Concerning the increase of PA level, “Games for Health” or “Exergames” requiring whole-body movements to control the game have been focused by numerous research projects. These studies show that Exergames have the potential to enhance physical fitness, at least at low levels (Peng, Lin & Crouse, 2011; Wiemeyer & Kliem, 2012). To improve health and fitness in a sustained manner, these games need to be designed in a way to ensure that players will be effectively engaged rather than quitting the game because of excessive demand or boredom.

The key problem in physical training is that identical workload (stress, i.e., defined external influences such as power, speed, etc.) can lead to different individual reactions in different organisms (strain). Therefore, the individual control of workload (stress) and strain is the key to an optimal adaptation of the organism during the physical training process.

To neither underchallenge nor overstrain the particular participant, an individual training control is important for an optimal adaptation and therefore essential for the success of the specific training.

The goal is to establish and immediately control individual workload by means of an adaptive algorithm using the example of a game-based endurance training. Hardy, Göbel, Gutjahr, Wiemeyer & Steinmetz (2012) developed a model addressing the relevant aspects for the development of such an Exergame (see Figure 4.1). The model distinguishes between static and adaptive aspects of user and game system.

Based on this model, the game “LetterBird” was implemented. The approach of this study aims at improving the training module, embedded in the adaptive part of the system as highlighted in Figure 4.1.

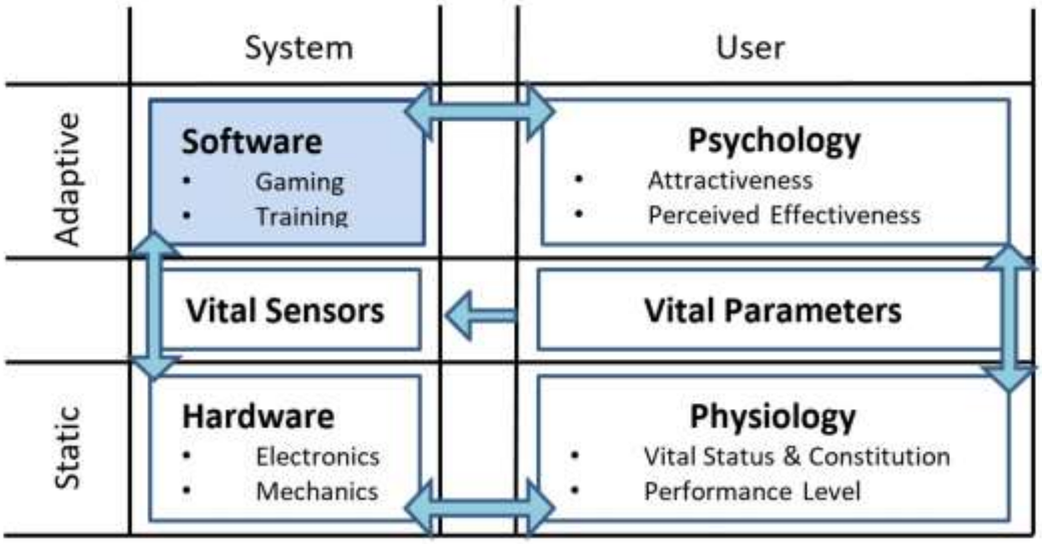

Figure 4.1 Refined Model of the relevant aspects for the development of Exergames (Hardy et al., 2012; see text for details).

4.3. Development of the algorithm

Various requirements from sport science need to be considered to develop an effective and efficient algorithm for the individualized and adaptive control of workload in endurance training.

When exercising, several physiological processes in the human organism are activated, ranging from the brain to the muscles. Therefore, numerous indicators can be used to measure physical workload. Among these, the heart rate (HR) is an often-used valid indicator of individual physiological workload that is easy to measure as compared to other possible indicators that can be applied to controlling a training process like oxygen uptake, hormones or lactate (Hebestreit, Lawrenz, Zelger, Kienast, & Jüngst, 2012). Different studies (e.g., (Vokac, Bell, Bautz-Holter, & Rohdal, 1975) show that in the range of submaximal workloads the increase of HR is linearly related to workload (i.e., exercise intensity). So, under certain conditions, the cardiopulmonary strain of the participant can be specifically controlled and an overload can be prevented by the use of submaximal HR.

Concerning appropriate training equipment, the usage of a cycle ergometer has advantages for cardio training. The weight of the participant is supported during the training process and a defined movement constrained by the limited (bio)mechanical degrees of freedom is performed. Therefore, the risk of injuries is reduced and a good comparability of the data is guaranteed (Hebestreit et al., 2012). To apply a cycle ergometer as training device in Serious Games, two purposes are required: control of training load and control of the game. In the game “LetterBird”, power (P) in W can be adjusted specifically and accurately, e.g., by varying resistance, and was therefore chosen as load parameter. Pedal rate (PR) was chosen for game control.

To ensure accurate control of workload by P, PR should be kept within a range that does not substantially influence workload. In this regard, Löllgen, Graham, & Sjogaard (1980) were able to demonstrate that at submaximal workloads (70% VO_{2max}) the PR on a cycle ergometer ranging from 40 revolutions per minute (RPM) to 80 RPM has only a small and non-significant effect on the HR. However, HR rises considerably at higher PRs (100 RPM). At maximal workload (100% VO_{2max}) PR has no effect at all. Because the HR is the parameter to be influenced, the game settings need to be adjusted accordingly to ensure that PR is well below 100 rpm.

A major problem with the control of training load via HR is that HR normally shows a delayed response to the onset of training bouts as well as to the change of training load (Ricardo, de Almeida, Franklin, & Araujo, 2005; Springer, Barstow, Wassermann, & Cooper, 1991).

Based on this evidence and original HR data provided by the Klinikum Darmstadt, an algorithm was developed controlling P of the cycle ergometer relative to the monitored HR of the participant.

The algorithm consists of two parts:

In the first part, the target load (P_{target}) evoking the required target HR ($HR_{training}$) is calculated using the measured data of the individual HR response at two defined load levels. Therefore, the target HR scope is set submaximal, ranging from 70 to 80 % of the maximal heart rate (HR_{max}; implemented in the game as target HR scope: $HR_{trainingScope}$ = 75%HR_{max} ±10 bpm). In the game, the target HR is calculated as 75% HR_{max}. The HR_{max} is calculated using the equation

- **Equation 4.1*: $HR_{max} = 220 - age$*** (Robergs & Landwehr, 2002).

The second part of the algorithm sets P of the ergometer according to P_{target} and, after a defined phase of adaptation, controls P depending on the actual HR of the participant. Provided that the $HR_{training}$ is reached or at least approached and due to the delayed response of the HR, control is set to adapt in steps of ±10 W every 30 s, if the HR leaves, i.e., exceeds or falls below, the target range. On the one hand, this procedure prevents an oscillation of the HR caused by the slow adaptation; on the other hand it avoids overloading the participant.

4.4. Method

In this two-phase pilot study participants performed a 4 min calibration phase to measure and calculate data required for the exercise phase. The goal of this study was to test the performance of the adaptation algorithm.

4.4.1. Participants

A convenience sample of four adults (2 men, 2 women, age: *range* = 26 – 56 yr., *M* = 41 yr., *SD* = 13.58, body weight: *M* = 73 kg, *SD* = 14.04) participated in this study. All participants reported to be healthy and to work out regularly at a non-competitive level. Demographical and anthropometric data is illustrated in Table 4.1.

Table 4.1 Demographic and anthropometric description of the participants – Manuscript I.

	Participant 1	Participant 2	Participant 3	Participant 4
Sex	male	female	male	female
Age [yr.]	53	29	56	26
Weight [kg]	80	70	90	52
Height [cm]	182	175	180	161
BMI	24.2	22.9	27.8	21.6
Smoker	no	no	yes	yes
$HR_{training}$[1] [bpm]	125	143	123	146

[1] Formula: $HR_{training} = 0.75 * (220 – age)$

4.4.2. Apparatus

All tests were performed on a cycle ergometer with a flywheel (Daum Ergometer 8008 TRS). Height and distance of the saddle were adjusted to the participant and kept constant throughout the study. The HR was monitored by a chest belt (POLAR, T31) and processed by the ergometer during the whole testing.

After starting the game “LetterBird” the HR data of the participant was logged and saved together with a corresponding timestamp, as well as P in W (measured by the ergometer) and PR (measured at the flywheel of the ergometer).

The ergometer settings only allow a differentiation in steps of 5 W, so the ergometer automatically rounds up or down. The ergometer is directly connected to a computer, where the software controlling the game “LetterBird” runs.

The goal of the game “LetterBird” is to collect randomly occurring letters with an animated pigeon. The approaching letters are differentiated into two types:

- Type 1: slow, score: 100 points
- Type 2: fast, score: 500 points

The altitude of the pigeon is controlled by the PR. With increasing PR the pigeon rises and if the PR is decreased, the pigeon sinks down. The PR range controlling the game is set to a range from 70 to 90 rpm. A higher or lower PR does not influence the game play: Below 70 rpm the pigeon stays at the bottom, beyond 90 rpm the pigeon flies at the top of the screen.

4.4.3. Procedure

The study was divided in two phases: calibration and exercise phase. Four participants passed a first tests series, whereas one participant was tested twice, i.e., repeated the calibration and exercise phase procedure after correction of the algorithm.

Calibration phase

After a short explanation about the game principle, the participants performed a 4 min calibration phase playing the game “LetterBird” at two successive load levels for 2 min each. The two load levels were adjusted depending on the BMI classification of the participant (normal weight vs. overweight):

- Normal weight (BMI ≦ 25):
  - Load Level 1 (P_{level1}) : 1 W/kg bodyweight (BW)
  - Load Level 2 (P_{level2}): 2 W/kg BW

- Overweight (BMI > 25):
  - Load Level 1: 0.5 W/kg BW
  - Load Level 2: 1 W/kg BW

While the measured data was analyzed and the required data calculated, the participant stopped exercising allowing the individual HR to return to pre-exercise levels.

Exercise phase

In the exercise phase, the participants again played the “Pigeon game” on the cycle ergometer at four different load levels. The first two load levels matched the load levels in the calibration phase; participants 1 and 2 played for 2 min per load level and participants 3 and 4 played for a shortened time (1 min) per load level.

All four participants performed at the third load level for one minute. At this load level, the P_{target} was set at the ergometer. The fourth and last load level represented the automatic load control (ALC), in which the ergometer controls and varies the load automatically according to the HR of the participant. The test was stopped after either 10 min or at a stable steady state at the target HR. The procedure is illustrated in Table 4.2.

Table 4.2 Illustrated procedure of the exercise phase after onset of the exercise.

	Timing procedure for participants 1 and 2 [min:sec]	**Timing procedure for participants 3 and 4 [min:sec]**
Load Level 1 (P_{level1})	0:00 – 1:59	0:00 – 0:59
Load Level 2 (P_{level2})	2:00 – 3:59	1:00 – 1:59
Calculated target load (P_{target})	4:00 – 4:59	2:00 – 2:59
Automatic load control (ALC)	5:00 – 10:00	3:00 – 10:00

4.4.4. Data processing

First, sex, age, weight, height, sports and smoking behavior were recorded. BMI was calculated using the formula

- **Equation 4.2:** $BMI = weight\ [kg] \,/\, height^2\ [m]$

to classify the participants into normal weight and overweight.

$HR_{training}$ was calculated using formula

- **Equation 4.3:** $HR_{training} = 75\%\ (220\text{-}age)$ (see Table 4.1).

Mean values (*M*) and standard deviation (*SD*) for HR over the last 60 s for every load level were calculated after the calibration phase. This data was used as HR for the corresponding load level. The target load evoking the target HR was calculated using the formula:

- **Equation 4.4:** $P_{target\_load} = BW * (P_{level2} + \frac{HR_{training} - (meanHR\ P_{level2})}{(meanHR\ P_{level2}) - (meanHR\ P_{level1})})$

M and *SD* for PR were calculated for the whole testing period for all data >0.

4.5. Results

The algorithm performed satisfactorily in the first two participants, whereas the target HR of the other two participants was reached after a transient increase beyond the tolerance. As an example, the data of one participant of each group (participants 2 and 4) is illustrated.

4.5.1. First test series ($N = 4$)

In the first two participants, $HR_{training}$ was reached as expected at the third load level of the exercise phase (P_{target}) and remained in a region of stable steady state. For participant 1, P_{target} even matched P_{level2}, so $HR_{training}$ was already reached in the calibration phase.

As expected, the HR showed an initial steep increase after the onset of exercise, followed by a leveling off in the course of the load level during the calibration phase. For participant 2 (see Figure 4.2), average values of the HR in the last 60 s of each load level were 118 bpm for P_{level1} (70 W) and 135 bpm for P_{level2} (140 W). P_{target} was 2.31 W/kg BW (≙165 W) expecting to evoke $HR_{training}$ of 143 bpm.

The mean PR for all valid data (values >0) was 80.69 rpm (*SD*=6.37).

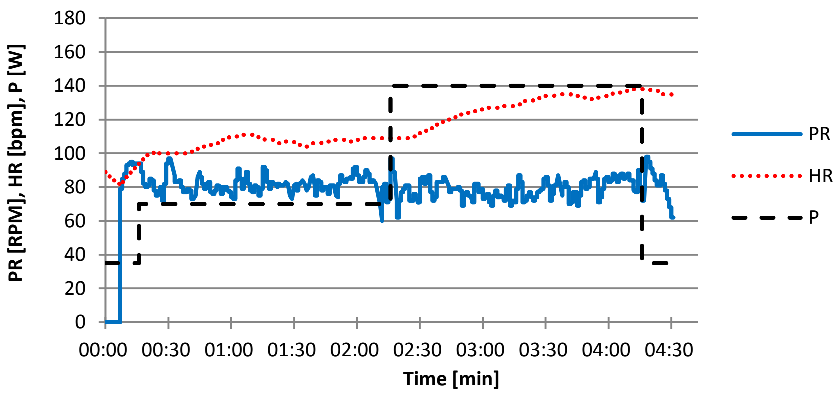

Figure 4.2 Calibration phase of participant 2.

The first minutes of the exercise phase replicated the calibration phase with a less fluctuating increase of the HR (see Figure 4.3). $HR_{training}$ was reached approximately 30 s after starting P_{target}. Mean HR of the last minutes was 138 bpm (*SD*=1.10), i.e., slightly beneath the $HR_{training}$

(mean deviation from $HR_{training}$: -4.87 bpm), but still in the intended training range (72% HR_{max}). An approach of $HR_{training}$ “from beneath” was still realized and an overload was prevented.

In the exercise phase mean PR was 80.8 RPM (SD=5.99) for valid data (values >0).

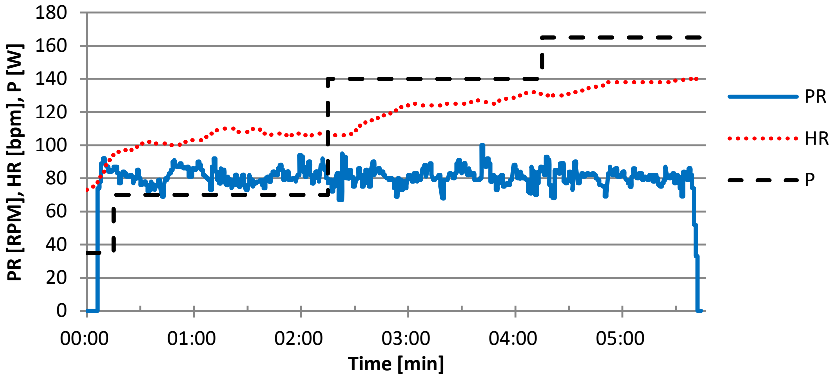

Figure 4.3 Exercise phase of participant 2.

In contrast, the analysis of the HR dynamics of participants 3 und 4 showed a different picture.

For participant 4, a continuous rise of the HR with no clear steady state of HR dynamics was found in the calibration phase (see Figure 4.4).

Nevertheless, average values of the last 60 s for each load level were calculated (P_{level1}: M = 118 bpm; P_{level2}: M = 152 bpm). This resulted in P_{target} of 1.81/kg BW (≙94.12 W). A higher PR range than required to control the game (M = 79.35 rpm, SD =9.22) was identified already in the calibration phase.

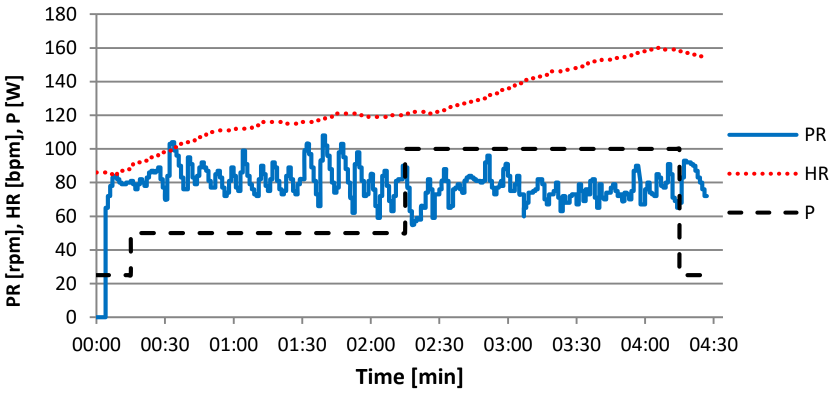

Figure 4.4 Calibration phase of participant 4.

A comparison of HR values in the exercise phase revealed considerable differences between participants 2 and 4. First, the HR recording in participant 4 was interrupted for 5 s (from 2:14 to 2:19) due to technical problems. Nevertheless, PR and P were still logged and due to the constant rise of the HR at this point the missing data could be interpolated.

Additionally, caused by the shortened duration of P_{level1} and P_{level2} causing a shortened adaptation time for the HR, the HR response was overshooting (Maximum HR during training: $HR_{max\_training}$ = 161 bpm, corresponding to 83,0% HR_{max}). A downward adjustment of two steps (in total 20 W) was necessary to reach $HR_{training}$ of 146 bpm (see Figure 4.5).

In participant 4, the exception occurred that P_{target} was beneath P_{level2}. Consequently, an approach of the $HR_{training}$ from beneath was rendered impossible.

However, average HR after P_{target} (2 min after onset until the end of exercise) (M = 155 bpm, SD = 3.67 bpm) was within the intended training range (79.7% HR_{max}).

Mean PR in the exercise phase (for data >0) was 79. 51 rpm (SD = 8.86).

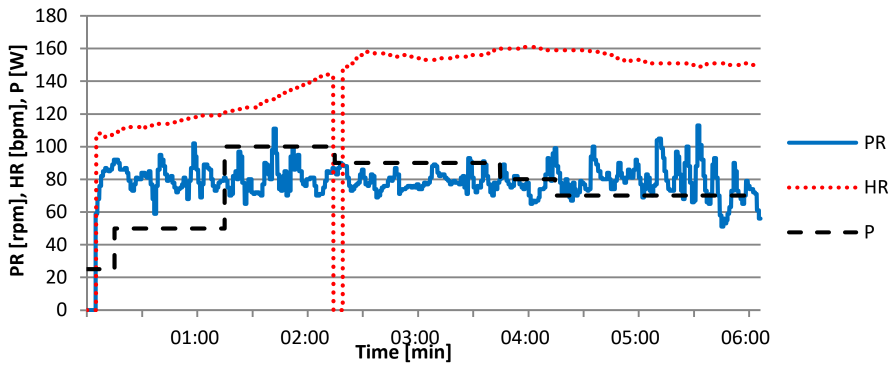

Figure 4.5 Exercise Phase of participant 4. Note a short period of interrupted recording of HR in the exercise phase.

4.5.2. Adjustments

Before further testing, the following adjustments were made to improve the approach towards the target HR:

- If the P_{target} is lower than P_{level2} of the calibration phase, P_{target} is substituted as load at P_{level2} in the exercise phase.
- A shortening of the load level duration turned out not to be suitable for the HR adaptation and is therefore set to two minutes. A slow and continuous adaptation to the workload is preferred.
- To minimize the risk of an excessive HR caused by a high PR level, P_{target} is subtracted by 10%. Possible efficiency issues, i.e., longer time to reach $HR_{training}$, are accepted in favor of the HR approach from beneath.
- The calculation of the average HR in load level 1 and 2 is reduced to the last 30 s of each load level, so the HR has enough time to adapt to the current workload.

4.5.3. Second test series (case study)

Participant 4 was tested again to validate the adjustments of the algorithm and to test the efficiency.

The calibration phase matched the calibration phase in the first test (see Figure 4.6). $HR_{max\_training}$ was lower (148 versus 161 bpm) than the $HR_{max\_training}$ in the first test. Average value of the HR in P_{level1} (118 versus 118 bpm) is comparable, but in P_{level2} mean HR was lower than in the first test (146 versus 152 bpm). Subtracting 10% of the calculated value resulted P_{target} of 1.79 W/kg BW (90 W).

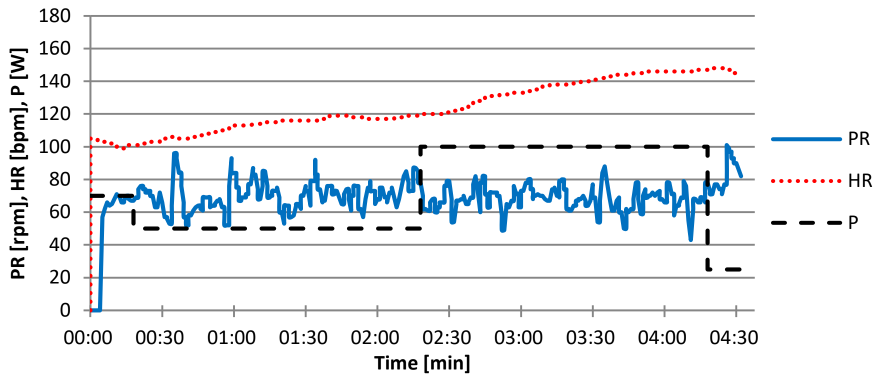

Figure 4.6 Calibration phase of participant 4 (second trial).

Due to the adjustments, HR followed the expected HR dynamics during the exercise phase (see Figure 4.7). A continuous rise of the HR towards the $HR_{training}$ was observed reaching a steady state after approximately four minutes from onset of exercise. Average HR during this steady state was 151 bpm (*SD* =1.61 bpm; range: *Minimum* =146 bpm, *Maximum* =155 bpm). The data also showed a two-step downward adjustment of P. Compared to the first test series this adaptation leads to a steady state of HR. As expected no overshooting or oscillations of the HR can be observed.

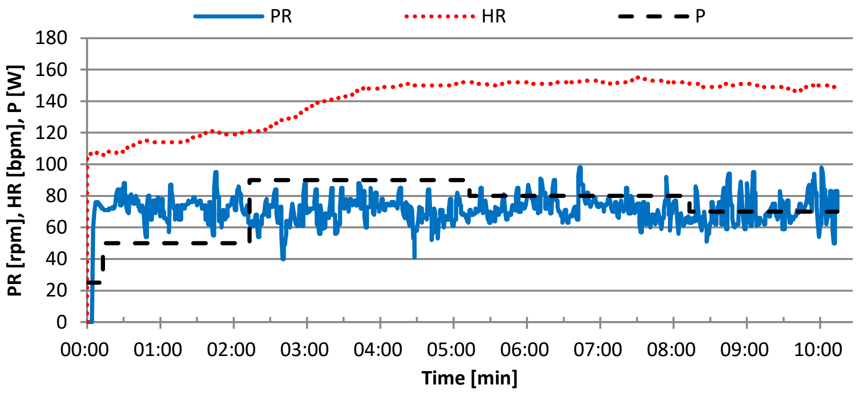

Figure 4.7 Re-testing of participant 4 with the adjusted algorithm (exercise phase).

4.6. Discussion

The aim of this study was to develop and test an algorithm for individual adaptive control of training load from a sport scientific point of view in the context of the Serious Game "LetterBird". In the first test series, in all four participants average HR was inside the expected target HR range from the beginning of ALC to the end of exercise. Nevertheless, the HR increased beyond the tolerances in two participants causing a successive downward adaptation of the algorithm for more than one step. This demonstrates that ALC reacted to the increasing HR and adapted the workload as expected; in this regard, the algorithm was working correctly. However, the aim of this research was to guide the actual HR towards $HR_{training}$ from beneath; this result was not established in two participants. Apparently, the calculation of P_{target} was not suitable for these two participants.

Compared to participant 1 and 2, participants 3 and 4 show several differences that may have caused the different HR response pattern:

- Smoking behavior:

Participants 3 and 4 are smokers, whereas participants 1 and 2 did not smoke.

- P_{target}:

Although all participants reported to be physically active, P_{target} of participant 1 and 2 was considerably higher than in participant 3 and 4, indicating a lower fitness level (participant 1: 180 W, participant 2: 165 W; participant 3: 95 W; participant 4: 90 W). Therefore, the influence of fitness level needs to be considered to adapt the algorithm. Particularly, personal reports on engagement in sports disciplines, average work out time per week and PA level at leisure may serve as indirect indicators of performance or fitness level.

- Shortened length of load level 1 and 2:

Participants 1 and 2 performed load level 1 and 2 in the exercise phase for 2 minutes, respectively. In contrast, participant 3 and 4 performed for only 1 minute at each load level.

In the adjusted version, technical sources of error leading to an incorrect calculation of P_{target} were corrected. Using this adapted formula calculating P_{target} appears to be a reasonable approach preventing an overshooting HR. $HR_{training}$ was evoked efficiently and effectively in the presented trial.

4.7. Conclusion

The results of the reported tests are promising. The data indicate that the developed algorithm, especially the adjusted version, is a reasonable approach to ensure an individual adaptive control of training load in the game “LetterBird”. Of course, the small sample is not representative, so further tests including different age, BMI, cycling experience and performance level (e.g., athletes versus non-athletes) are needed to prove the effectiveness and efficiency of the algorithm.

A problem not yet solved is the influence of PR used to control the pigeon on the HR. Therefore, a further study is required to test the influence of these large short-term oscillations on HR dynamics.

Furthermore, the question has to be addressed, if the preferred PR of the participants has an influence on the HR. Previous studies on preferred PR confirm that the preferred PR exceeds the most efficient one (Kohler & Boutellier, 2005).

In the future, the algorithm is intended to be integrated into a long-term training plan, taking into account the current physical condition to enable an optimal and individualized adaptation to training.

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5. Manuscript II: Personalized Adaptive Control of Training Load in Cardio-Exergames – a Feasibility Study

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Author contribution

Katrin Hoffmann is the main and corresponding author of this article responsible for the conception and design of the study and writing of the manuscript. Josef Wiemeyer was the supervisor of the project and contributed in discussions regarding interpretation of the results and writing the paper. Sandro Hardy was responsible for the development of the applied Exergames. Stefan Göbel was the supervisor of the development of the applied Exergame.

5.1. Abstract

Objective: This paper presents a feasibility study of using an algorithm for an individual and adaptive control of training load in an ergometer-controlled exergame for aerobic training. An additional goal was to investigate the effects of the adaptive game on the players' motivation.

Materials and Methods: A two-phase approach (calibration and exercise phase) was applied in a sample of 16 physically active adults. In the cardio exergame "LetterBird", the flight of a pigeon was controlled by the pedaling rate of a bike ergometer as input device. During the calibration phase the individual heart rate (HR) responses of the players were measured. In the exercise phase, this data was used to adjust the resistance of the ergometer using the proposed algorithm. The purpose of this algorithm was to induce an individually defined target heart rate and to keep it in a steady state. In order to establish a reference for further studies, the game experience was measured using the kids-Game Experience Questionnaire.

Results: In 15 of 16 participants the actual HR reached the intended individual HR range within 10 minutes after onset of exercise. However, the induced HR initially exceeded the target HR in 13 participants which made load adjustments necessary. The analysis of the *kids-Game Experience Questionnaire* confirmed the motivational effect of the exergame "LetterBird".

Conclusion: The results confirm that the proposed algorithm for personalized heart rate control in the game "LetterBird" is feasible. Furthermore, the cardio exergame "LetterBird" seems to have a substantial short-term motivating effect.

5.2. Introduction

All over the world the current state of public health calls for more personal investment in health-enhancing activities. Among others, an important goal is to increase physical activity in (apparently) healthy people of all ages to reduce risks of cardio-vascular diseases (WHO, 2010; ACSM, 2011). However, establishing sustainable changes in health-enhancing physical activity is challenging as it depends on numerous factors including the quality of the program as well as social, psychological, and physiological factors. In this regard, Serious Games may be an attractive option. Stated to be "more than fun" (Göbel, Hardy, Wendel, Mehm, & Steinmetz, 2010), Serious Games aim at a double and challenging mission: accomplishing a serious goal with high motivation and strong engagement. Exergames, i.e., digital games requiring whole-body exercises to control the game, may have the potential to be used as an efficient and effective tool to promote an increased level of physical activity (Wiemeyer & Kliem, 2012, Peng, Crouse, & Lin, 2013; Pent, Lin, & Crouse, 2011).

The Exergame technology platform StoryTecRT (Hardy, Göbel, & Steinmetz, 2013) has been developed as a theoretical framework for the personalization and adaptation[1] of exergames (Göbel et al., 2010; Hardy, Göbel, Wiemeyer, & Steinmetz, 2012). The cardio training application ErgoActive, based on this platform, allows the adaptation of single game elements and training concepts while keeping all other parameters at a defined level.

[1] Note that the term „adaptation" is used with two different meanings: Computer science uses „adaptation" to denote changes the computer technology makes to adjust to the specified requirements, e.g., dynamic difficulty adaptation. Sport science uses the term to denote functional and structural changes of the organism as a response to training load. For clarity we always use the term "functional and structural adaptations" to indicate this second meaning.

Such adaptations are, on the one hand, important to maintain the player's motivation and interest in the game. Balancing task difficulty and fitness level supports motivation and therefore preserves the attractiveness of the games at the same time (Sinclair, Hingston, Masek, & Nosaka, 2010).

On the other hand, adaptations increase the effectiveness of exercise. From the perspective of sport science, optimal functional and structural adaptation to training requires individually optimal strain on the human body (Bouchard & Rankinen, 2001). Inducing this optimal strain is difficult. Numerous external and internal influences, such as cycling resistance and cadence or age and performance level, induce individually varying internal responses like increasing heart rate (HR) and oxygen uptake (VO_2). These individual responses are moderated by environmental and genetic influences (Bouchard & Rankinen, 2001).

In this paper, we focus on the adaptive control of HR responses in cardio training. The HR is a valid measurement of individual responses to aerobic training. Whereas HR has often been measured in exergames (Peng et al., 2013; Peng et al. 2011), there seem to be no studies that focus on methodologies to influence and control the HR according to training prescriptions.

This paper presents a study which was performed to evaluate an algorithm providing an optimized training based on current HR responses. Therefore, a calibration routine was applied prior to the exercise phase. The purpose of the developed algorithm is to guide the individual HR of every single player into a prescribed HR range within a short period of time and to keep it within this range while playing. Therefore, the difference between the actually measured and the intended HR was analyzed. The following questions were addressed:

Can the results of the calibration phase be replicated?

Can the algorithm guide the HR of the participants into a defined target HR zone?

Is the algorithm able to correct the training load in case of a deviation of more than 5 bpm to finally reach the intended HR within 10 min after the beginning of exercise?

Does the HR stay within the expected training range?

How is the subjective game experience of the cardio exergame "Letterbird" regarding the seven dimensions challenge, competence, flow, immersion, negative affect, positive affect, and tension?

This approach was applied as a feasibility study to estimate parameters needed to design a main study, e.g., procedure of the treatment, recruitment, methods and acceptability (Bowen et al., 2009, Leon, Davis, & Kraemer, 2011; Kraemer, Mintz, Noda, Tinklenberg, & Yesavage, 2006, Thabane et al., 2010). While there is no consensus concerning the application of inferential statistics in pilot and feasibility studies (Leon et al., 2011; Arain, Campbell, Cooper, & Lancaster, 2010), we used statistics to explore rather than test hypotheses due to the lack of knowledge addressing HR control in exergames. No fixed sample size was calculated a priori to ensure incremental methodology.

5.3. Materials and Methods

The presented study was part of the interdisciplinary project "Technology-supported measurement and evaluation of the efficacy and acceptance of Serious Games for sport and health”. The project has been approved by the Ethics Committee of Technical University of Darmstadt in 2012.

5.3.1. Participants

Seventeen physically active adults (10 males, 7 females) volunteered to participate in this study after signing an informed consent. One male participant was excluded due to calculation errors during the trial.

The weight of the participants was classified into normal weight and overweight depending on the body mass index (BMI) (normal weight: BMI ≦ 25 kg/m^2, overweight: BMI > 25 kg/m^2). Additionally, the lifestyle of the participants was classified depending on their physical activity (PA) level. Participants with a workout time of less than 3 hours per week were classified as sedentary, while the remaining participants were classified as active. This cutoff criteria for active versus sedentary lifestyle was chosen considering the volumes recommended by ACSM (2011) and WHO (2010).

No participant worked out less than 1.5 hours per week or more than 6 hours per week, respectively. 13 of 16 participants were members of a sports club.

The participants’ characteristics are described in Table 5.1.

Table 5.1 Demographic and anthropometric description of the participants – Manuscript II.

	Males (n=9)			**Females (n=7)**			**Total (n=16)**		
	M	***SD***	***Range***	***M***	***SD***	***Range***	***M***	***SD***	***Range***
Age [yrs]	26.6	4.45	13	33.4	10.49	31	29.6	8.18	31
Height [m]	1.84	0.06	0.21	1.73	0.06	0.15	1.80	0.09	0.28
Weight [kg]	81.1	7.10	20	65.0	5.72	18	74.1	10.40	38
BMI [kg/m^2]	22.9	1.78	5.2	21.8	1.37	4.2	22.9	1.78	7.1

5.3.2. Apparatus

The exergame “LetterBird” used in this study is part of a set of mini games developed with the application ErgoActive (Hardy, Dutz, Wiemeyer, Goebel, & Steinmetz, 2014; Hardy, Goebel, Gutjahr, Wiemeyer, & Steinmetz, 2012). “LetterBird” allows controlling the exergame with a bicycle ergometer as input device (see Figure 5.1). Therefore, the player controls the altitude of a flying bird by means of the pedal rate (PR). By adjusting the PR the bird can fly at higher and lower altitudes and collect letters to earn points (see Figure 5.1). The underlying framework StoryTecRT allows exchanging assets, and, among other parameters, to set PR limits controlling the pigeon as well as the resistance of the bike while playing according to predefined training plans.

Figure 5.1 Left side: participant playing the "LetterBird" using a bike ergometer as input device; right side: screenshot of the minigame "LetterBird".

All tests were performed on a cycle ergometer (Daum 8008 TRS 3) with a flywheel. The height of the saddle was adjusted to the participant's leg length at the beginning of the test. The HR was monitored using a chest belt (Polar, T31). The Power (P) was controlled by the resistance at the flywheel and measured in Watts (W) by the ergometer. PR was measured in revolutions or rates per minute (rpm) at the flywheel. The PR limits for controlling the pigeon were set to a range of 60 to 80 rpm. This variance of PR was expected to have no significant influence on the HR (Loellgen, Graham, & Sjogaard, 1980).

All values were processed by the ergometer cockpit and logged in a text file together with the corresponding time stamp (in milliseconds).

Data recording was started with the launch of the software.

5.3.3. Description of the algorithm

SI Units were used for data processing and calculating.

The approach presented in this paper is based on a pilot study (Hoffmann, Wiemeyer, Hardy, & Göbel, 2014) which focused on testing the calibration routine of an algorithm to provide an optimized training based on current HR responses.

The feasibility study presented in this paper was divided into two phases: the calibration and the exercise phase (see Figure 5.2).

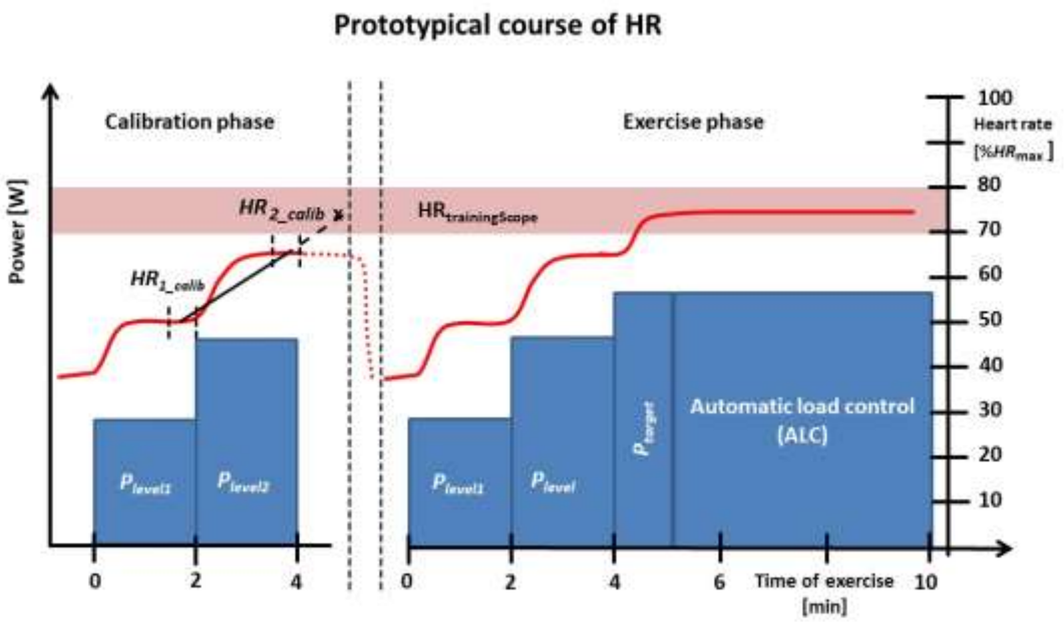

Figure 5.2 Prototypical course of the HR during the calibration and exercise phase of the pilot testing of the algorithm. In the figure, the standard procedure is illustrated.

Before starting the calibration phase, the individual target heart rate was calculated as intended exercise HR ($HR_{training}$) for submaximal training (Robergs & Landwehr, 2002; Goldberg, Elliot, & Kuehl, 1988). Equations 5.1 and 5.2 were used:

- **Equation 5.1:** $HR_{max} = 220 - age$
- **Equation 5.2:** $HR_{training} = 0.75 * HR_{max}$

Legend:
HR_{max}: *maximum HR depending on age [beats per minute, bpm]*
$HR_{training}$: *intended exercise HR for submaximaltraining, target heart rate [bpm]*

During the calibration phase, the participants played the game “LetterBird” at two successive load levels (P_{level1}, P_{level2}) for 2 minutes each. The individual HR response to these load levels was measured and averaged over the last 30 sec of each load level (HR_{1_calib}, HR_{2_calib}).

The load was calculated individually depending on the bodyweight (BW) of the participants corresponding to the recommendations for cycle ergometry. A differentiation between normal weight and overweight participants regarding the BMI was advised. However, athletes can have a misleading BMI result due to the higher mass of muscle fibers. Therefore, the load was set according to the BMI and PA level, respectively.

- **Equation 5.3a:** $P_{level1} = x_1 * BW$
- **Equation 5.3b:** $P_{level2} = x_2 * BW$

Legend:
P_{level1}, P_{level2} *work load in load level 1 and 2 [Watt, W]*
$x_1; x_2$ *relative load [W/kg]*
BW *body weight [kg]*

The relative load for overweight participants with a sedentary lifestyle was set to:

- **Equation 5.3c$_1$:** $x_1 = 0{,}5 \frac{W}{kg}$
- **Equation 5.3c$_2$:** $x_2 = 1 \frac{W}{kg}$

The relative load for all other participants was set to:

- **Equation 5.3d$_1$:** $x_1 = 1 \frac{W}{kg}$
- **Equation 5.3d$_2$:** $x_2 = 2 \frac{W}{kg}$.

In the range of submaximal workloads, the increase of the HR is considered to be linearly related to the workload (Vokac, Bell, Bautz-Holter, & Rohdal, 1975) (see Figure 5.2). Based on this linear extrapolation, the target workload ($P_{target\_estimated}$) evoking $HR_{training}$ was calculated (see equation 5.4, solved for L_{est} in equation 5.5).

- **Equation 5.4:** $\frac{P_{target\_estimated} - P_{level\ 2}}{P_{level\ 2} - P_{level\ 1}} = \frac{HR_{training} - HR_{2\_calib}}{HR_{2\_calib} - HR_{1\_calib}}$

- **Equation 5.5:** $P_{target\_estimated} = \left(\frac{HR_{training} - HR_{2\_calib}}{HR_{2\_calib} - HR_{1\_calib}}\right) * (P_{level\ 2} - P_{level\ 1}) + P_{level\ 2}$

Legend:

$P_{target\_estimated}$:	*estimated work load evoking the target heart rate [W]*
HR_{1_calib}:	*mean HR averaged over the time period 1:30 – 2:00 min after onset of exercise*
HR_{2_calib}:	*mean HR averaged over the time period 3:30 – 4:00 min after onset of exercise*

Additionally, the workload was reduced by 10%, to prevent an overload of the participant due to miscalculations induced by an incorrect classification of the participant (P_{target}; see Equation 5.6).

- **Equation 5.6:** $P_{target} = P_{target\_estimated} * 0.9$

Legend:

$P_{target\_estimated}$:	*estimated work load evoking the target heart rate [W]*
P_{target}:	*work load set at the ergometer [W]*

Depending on the HR data obtained in the calibration phase, two different procedures were used in the exercise phase:

- In the *standard procedure*, the first four minutes of the calibration phase with the load levels P_{level1} and P_{level2} were repeated in the exercise phase. Thus, the results of the calibration phase were verified and the HR was slowly increased to the desired value.
- The *exception procedure* was used when the second load level (P_{level2}) in the calibration phase induced a HR higher than $HR_{training}$. In this case, P_{target} substituted P_{level2} in the exercise phase.

Beginning with the fifth minute, the algorithm switched to the automatic load control (ALC; see Figure 5.2). In this mode, P_{target} was administered and automatically adjusted in real-time if required: If the current HR was outside the range of the predefined HR the algorithm automatically increased or reduced the load level by 10 W every 60 sec. The exact load schedule is illustrated in Table 5.2.

Table 5.2 Load schedule in the exercise phase after onset of exercise.

Time [min:sec]	Standard procedure	Exception procedure
0:00 – 1:59	Load level 1 (P_{level1})	Load level 1 (P_{level1})
2:00 – 3:59	Load level 2 (P_{level2})	Calculated target load (P_{target})
4:00 – 4:59	Calculated target load (P_{target})	Calculated target load (P_{target})
5:00 – 10:00	Automatic load Control (ALC)	Automatic load Control (ALC)

Figure 5.2 shows a prototypical course of load level and HR for this study. The predefined HR limit for a load adaptation within the ALC was set to $HR_{training}$ ± 5 bpm. Thus, the load was expected to be adapted before the HR actually exceeded the intended training range of 70 to 80 % HR_{max}.

During the testing phase the unduly long overpassing HR data of participant 6 made an immediate readjustment of the algorithm necessary: Starting with participant 7 the adaptation in the ALC was reduced from every 60 sec to every 30 sec to ensure a faster response to an HR exceeding the prescribed range.

5.3.4. Game Experience

Immediately after the exercise, all participants completed the German version of the kids-Game Experience Questionnaire (kids-GEQ; Poels, IJsselsteijn, & deKort, 2008). This instrument comprises seven dimensions of game experience, i.e., flow, challenge, competence, tension, negative affect, positive affect, and immersion, addressed by 3 items each (score: five-point scale).

The kids-GEQ was used as it is based on the Game Experience Questionnaire (Poels et al., 2008; Nacke, 2009) for adults covering all relevant dimensions of game experience. Furthermore, the kids-GEQ uses a child friendly format and wording. It was applied to ensure comparability to future studies planned with children.

5.3.5. Data Exploration

In this feasibility study statistical analysis was used for exploration.

Mean HR for a period of 30 sec was calculated to compensate the HR fluctuations caused by the game (i.e., varying PR for game control, or motivational aspects causing arousal).

The following research questions were investigated:

Can the results of the calibration phase be replicated?

Reliability of the HR response to the defined load levels was tested by comparing the obtained HR data at the end of each load level in calibration (HR_{1_calib}, HR_{2_calib}) and exercise phase (HR_{1_exer}, HR_{2_exer}) using equation 5.7, 5.8a and 5.8b.

In the exception procedure, different load levels and therefore different HR responses were found in the first four minutes of the calibration and exercise phase. Therefore, HR_{2_calib} in the calibration phase was compared to $HR_{training}$ using equation 5.8b.

The following calculations were performed:

Calculation of ΔHR_1:

- **Equation 5.7: $\Delta\ HR_1 = HR_{1\_calib} - HR_{1\_exer}$**
  with
  HR_{1_calib}: mean HR from 1:30 min to 2:00 min in the calibration phase
  HR_{1_exer}: mean HR from 1:30 min to 2:00 min in the exercise phase

Calculation of ΔHR_2:

- **Standard – Equation 5.8a: $\Delta\ HR_2 = HR_{2\_calib} - HR_{2\_exer}$**
  with
  HR_{2_calib}: mean HR from 3:30 min to 4:00 min in the calibration phase
  HR_{2_exer}: mean HR from 3:30 min to 4:00 min in the exercise phase
- **Exception – Equation 5.8b: $\Delta\ HR_2 = HR_{training} - HR_{2exer}$**
  with
  $HR_{training}$: target heart rate
  HR_{2_exer}: mean HR from 3:30 min to 4:00 min in exercise phase

Furthermore, Mean and SD were calculated for the deviations. A one-sample t-test was calculated to check if the values differed significantly from zero. Reliability of the HR responses to the corresponding load level was tested using a test-retest correlation

Mean, Range and SD of the HR data were calculated for different time periods testing the reliability of the calculated target load and the following ALC in the exercise phase. Therefore, the difference (ΔHR) between the target and the actual heart rate were evaluated. A positive value indicates that the actual HR exceeds the target HR. Each time period was chosen to investigate the corresponding research question.

1. *Can the calculated load guide the HR of the participants to the target HR zone ($HR_{training}$ ± 5 bpm)?*

Time Period 0 defines the time when P_{target} was set at the ergometer.

Time Period 1 (TP_1) defines the time when HR was expected to have reached $HR_{training}$ zone. Therefore, TP_1 was set to 5:00 min – 5:30 min after onset of exercise for the standard procedure and to 3:00 min – 3:30 min after onset of exercise for the exception procedure.

2. *Is the algorithm able to correct the training load in case of a deviation of more than 5 bpm to finally reach $HR_{training}$ within 10 min after the beginning of exercise?*

Time Period 2 (TP_2) was set to 9:30 min and 10:00 min after onset of exercise.

3. *Does the HR stay within the expected training range of 70 to 80% HR_{max}?*

To answer this question, Time Period 3 (TP_{ALC}) was defined to investigate the mean HR measured over the time when HR is expected to have reached the target HR zone to the end of exercise. In the standard procedure TP_{ALC} was set to 5:00 min to 10:00 min after onset of exercise. In the exception procedure TP_{ALC} was set to 3:00 min to 10:00 min after onset of exercise.

4. *How is the subjective game experience of the cardio exergame "Letterbird" regarding the seven dimensions challenge, competence, flow, immersion, negative affect, positive affect, and tension?*

In addition to the means and standard deviations of the kids-GEQ scores, reliability of the seven dimensions was calculated. Therefore, Cronbach's Alpha was calculated for three items per dimension.

5.4. Results

The participants were classified according to the mode of procedure (standard vs. exception procedure) and the number of adaptation steps needed to guide the HR into the target zone during the ALC. The results are displayed in Table 5.3.

The HR courses depending on the classification of the participant are illustrated in

Figure 5.3.

Table 5.3 Number of load steps during the ALC in the standard and the exception procedure.

Procedure	**Sex**	**Number of load adjustments**				
		0	**1**	**2**	**>2**	**total**
Standard Procedure	male	0	1	0	4	5
	female	0	0	0	1	1
	Total	0	1	0	5	6
Exception Procedure	male	1	2	1	0	4
	female	2	1	1	2	6
	Total	3	3	2	2	10
Total		**3**	**4**	**2**	**7**	**16**

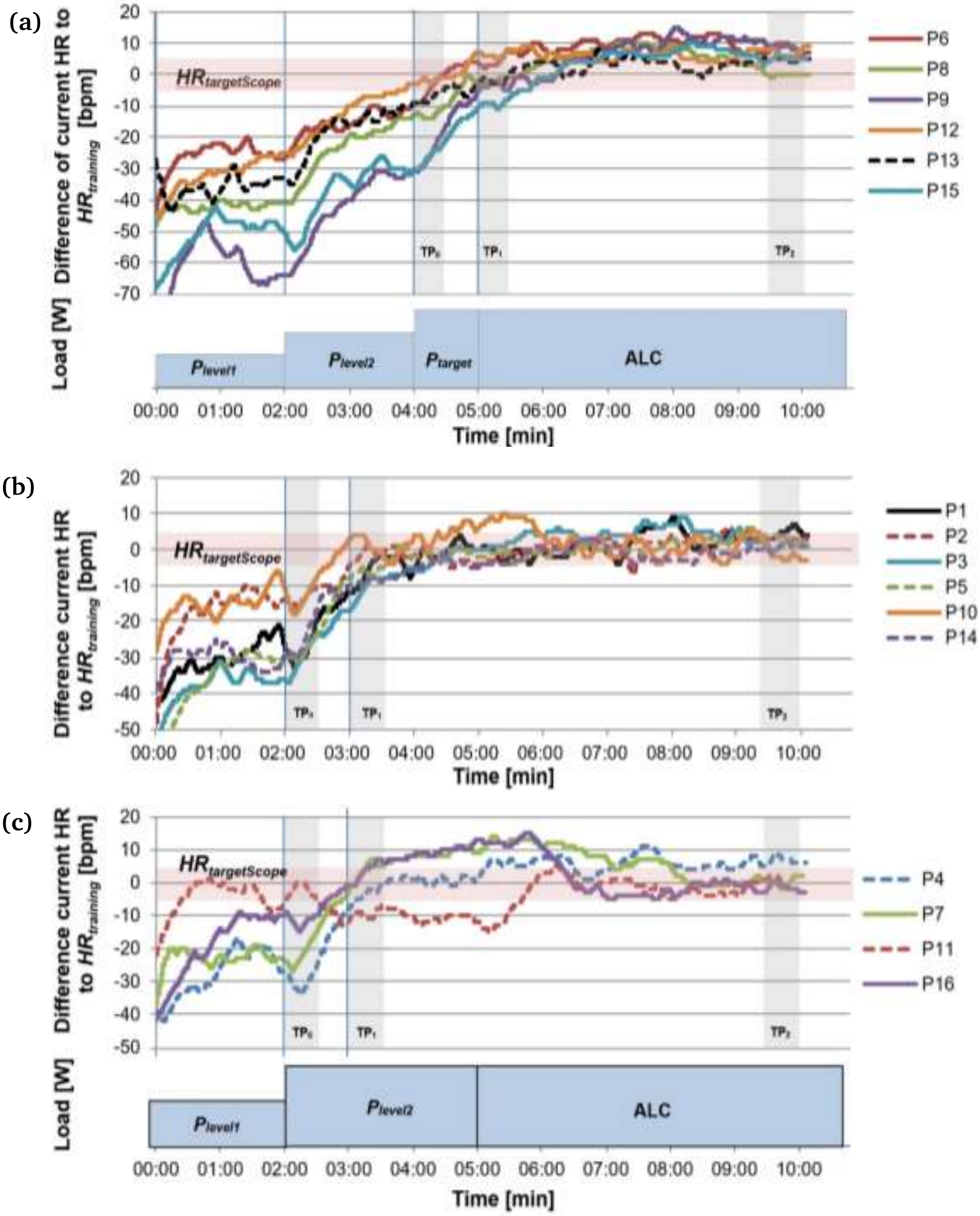

Figure 5.3 (a) Standard procedure. The dotted line represents the participant with only one adaptation step; solid lines represent participants with more than two adaptations during the automatic load control. (b) Exception procedure, fewer than two adaptation steps. Dotted lines represent participants with no adaptation; solid lines represent participants with one adaptation step during the automatic load control. (c) Exception procedure, two or more adaptation steps. Dotted lines represent participants with two adaptations steps; solid lines represent participants with three adaptations steps during the automatic load control. Load changes in the particular load levels are represented schematically. TP_0 – TP_2 represent the defined time points for heart rate (HR) measurement, For the standard procedure, TP_0 is 4:00–4:30 minutes, TP_1 is 5:00–5:30 minutes, and TP_2 is 9:30–10:00 minutes; for the exception procedure, TP_0 is 2:00–2:30 minutes, TP_1 is 3:00–3:30 minutes, and TP_2 is 9:30–10:00 minutes. bpm: beats per minute; P_{target}: calculated target load; $HR_{targetScope}$: heart rate during exercise; P_{level1}: load level 1, P_{level2}: load level 2.

In total, 48 load adaptation steps were realized. Most of them (44 of 48; 91.7%) reduced the load level. An increase could be found only in two participants.

P_{target} was considerably higher in the standard procedure (*Mean* = 204.93 W, *Max* = 252.27 W, *Min* = 166.52 W, *SD* = 27.48) compared to the exception procedure (*Mean* = 120.55 W, *Max* = 177.14 W, *Min* = 39.16 W, *SD* = 38.59).

Can the results of the calibration phase be replicated?

The HR courses of the calibration phase were not completely replicated in the exercise phase. However, only minor HR deviations were found. The mean deviations were not significantly different from zero in both load levels (ΔHR_1: p = .03; ΔHR_2: p = .13). In only two cases the HR in the exercise phase differed from the HR in the calibration phase by more than 10 bpm. High test-retest correlations (r_{tt} > .85) were found. All results are presented in Table 5.4.

Table 5.4 Comparison of the mean HR data of the calibration and exercise phase over the last 30 sec of each load level (HR_{1_Calib}/HR_{1_exer}: 1:30 min - 2:00 min after onset of exercise, HR_{2_calib}/HR_{2_exer}: 3:30 min - 4:00 min after onset of exercise, $HR_{training}$: estimated HR in case of exception procedure).

		Calibration Phase			Exercise Phase		ΔHR_1 [a]	ΔHR_2 [b]
ID	Procedure	HR_{1_calib}	HR_{2_calib}	$HR_{training}$	HR_{1_exer}	HR_{2_exer}		
1	Exception	114		148	124	144	- 10	4
2	Exception	129		143	129	142	0	1
3	Exception	101		137	101	130	0	7
4	Exception	109		137	117	140	- 8	7
5	Exception	121		147	117	146	4	1
6	Standard	110	127		118	132	- 8	- 5
7	Exception	116		150	128	157	- 8	- 7
8	Standard	100	125		100	127	0	- 2
9	Standard	81	109		84	117	- 3	- 3
10	Exception	122		143	132	142	- 10	1
11	Exception	134		127	121	118	13	9
12	Standard	109	132		117	138	- 8	- 6
13	Standard	107	132		114	137	- 7	- 5
14	Exception	114		145	112	140	2	5
15	Standard	93	119		101	119	- 8	0
16	Exception	111		135	124	142	- 13	- 7
r_{tt}	HR_1						.856	
	HR_2							.890

[a] $\Delta HR_1 = HR_{1\_calib} - HR_{1\_exer}$
[b] $\Delta HR_2 = HR_{2\_calib} - HR_{2\_exer} / \Delta HR_2 = HR_{training} - HR_{2\_exer}$

Can the calculated load guide the HR of the participants to the target HR zone ($HR_{training}$ ± 5 bpm)?

At TP_1, only minor deviations between the actual and the intended HR can be found (*Mean* = -3.12 bpm; *SD* = 5.38; *Range* = 17.07 bpm). Four of 16 participants showed an increase of the HR above $HR_{training}$ already at TP_0.

HR data for all time points are illustrated in Table 5.5.

Table 5.5 HR data at defined time periods for all participants (TP_0: onset of target load; TP_1: 1 minute after onset of target load; TP_2: end of exercise; TP_{tot}: 1 minute after onset of target load to end of exercise).

ID	TP_0	$\Delta HR_{TP0/exer}$	TP_1	$\Delta HR_{TP1/exer}$	TP_2	$\Delta HR_{TP2/exer}$	TP_{tot}	$\Delta HR_{tot/exer}$
1	119.74	-28.26	141.13	-6.87	151.07	3.07	148.44	0.44
2	129.55	-13.45	141.59	-1.41	146.38	3.38	143.50	0.50
3	106.62	-30.38	126.23	-10.77	139.71	2.71	138.20	1.20
4	108.97	-30.03	135.18	-3.82	145.16	6.16	143.05	4.05
5	118.52	-28.48	140.76	-6.24	151.84	4.84	144.24	-2.76
6	139.13	-04.87	149.29	5.29	151.28	7.28	153.17	9.17
7	129.96	-22.04	153.35	-3.35	150.38	0.38	156.12	6.12
8	129.30	-12.70	140.13	-1.87	144.45	2.45	146.48	4.48
9	124.89	-24.11	146.37	-2.63	159.51	10.51	146.54	-2.46
10	129.27	-13.73	145.18	2.18	146.40	3.40	145.06	2.06
11	124.59	-02.41	117.23	-9.77	125.90	-1.10	122.39	-4.61
12	141.33	-01.67	149.30	6.30	150.58	7.58	149.25	6.25
13	140.92	-07.08	146.07	-1.93	151.97	3.97	150.84	2.84
14	119.40	-25.60	135.99	-9.01	144.68	-0.32	142.63	-2.37
15	122.81	-26.19	139.74	-9.26	154.45	5.45	152.29	3.29
16	123.36	-11.64	138.27	3.27	133.27	-1.73	138.20	3.20

Is the algorithm able to correct the training load in case of a deviation of more than 5 bpm to finally reach $HR_{training}$ within 10 min after the beginning of exercise?

In 11 of 16 trials the HR was within the intended range ($HR_{training}$± 5 bpm) at TP_2. Four participants showed an increase of the HR above the intended range. Only one participant exceeded the intended training range with 80.6% HR_{max}. ($HR_{training}$ + 10.51 bpm; averaged over 30sec). Mean values for all participants were 77.0 %HR_{max} (*SD* = 1.74; *Range* = 6.52%) (see Table 5.5).

Does the HR stay within the expected training range of 70 to 80% HR_{max}?

In general, a positive ΔHR was observed indicating that the actual HR exceeded $HR_{training}$, especially in the standard procedure. Nevertheless, an approximation of the HR courses towards $HR_{training}$ during the training process could be found in all participants. For TP_{tot} the maximum positive deviation of HR from $HR_{training}$ was 15 bpm (83.3% HR_{max}). The mean HR averaged over the ALC was within the expected training range in all participants (see Table 5.5).

How is the subjective game experience of the cardio exergame "Letterbird" regarding the seven dimensions challenge, competence, flow, immersion, negative affect, positive affect, and tension?

The results of the scores measured by the kids-GEQ are illustrated in Figure 5.4. Only negative affects and tension were rated low. Positive affects, challenge, flow, and competence were rated high, i.e. about 3 meaning substantial game experience. Immersion was rated as moderately. The questionnaire was accepted very well. Reliability varied between subscales (Challenge: α = .235; Competence: α = .877; Flow: α = .501; Immersion: α = .92; Negative Affect: α = .216; Positive Affect: α = -.128; Tension: α = .304).

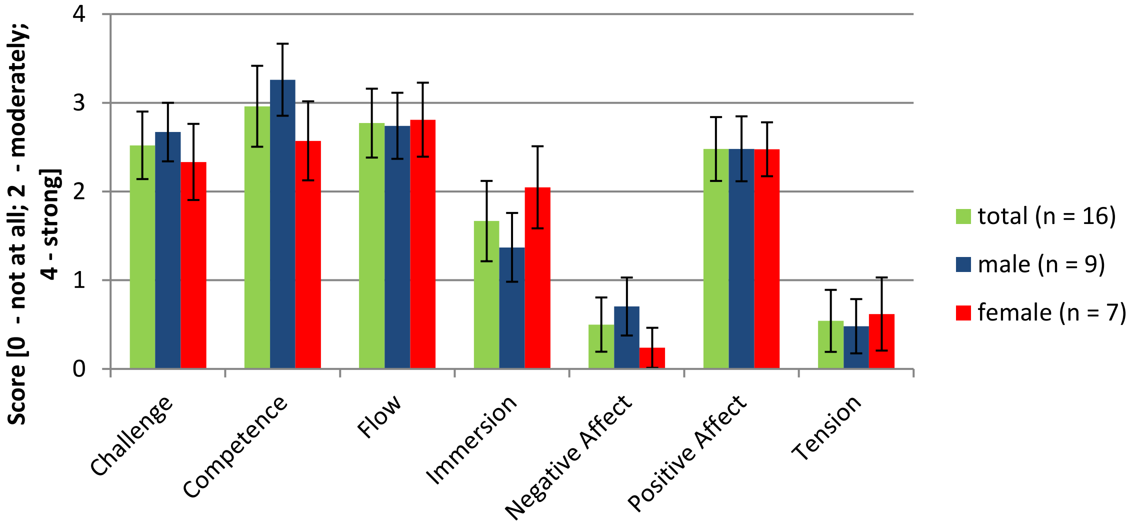

Figure 5.4 Scores of the seven game experience dimensions measured by the kids-GEQ.

5.5. Discussion

In this study, the feasibility of a using a modified algorithm for individualized control of load was tested in a cardio exergame.

The study confirmed that it is possible to guide the individual HR of the tested participants towards a given HR range within the setting of the cardio exergame "LetterBird". Therefore, an individual and optimal training is possible. However, a transitional overpassing HR response was still observed. Due to the delayed HR response this exceeding cannot be ruled out by controlling the load level exclusively by the current HR using the present algorithm.

Suggestions to improve the algorithm

In 10 of 16 cases, the exception procedure was used. This leads to the conclusion that P_{level2} with 2 is very likely inducing a HR above $HR_{training}$.

The classification of the participants needs to be improved and the calibration phase has to be adapted accordingly. We propose the mean load data of the females at the end of the exercise phase as load suitable for most participants. The following classification is suggested:

For normal weight participants who either have a sedentary lifestyle or an active lifestyle without performing endurance sport (i.e., running, swimming, cycling) the following load levels are specified:

- **Equation 5.3e₁:** $x_1 = 1\ \frac{W}{kg}$
- **Equation 5.3e₂:** $x_2 = 1.4\ \frac{W}{kg}$

The load for overweight participants with a sedentary lifestyle is retained:

- **Equation 5.3f₁:** $x_1 = 0.5\ \frac{W}{kg}$
- **Equation 5.3f₂:** $x_2 = 1\ \frac{W}{kg}$

The load for normal weight participants with a physically active lifestyle and exercising endurance sport is specified as

- **Equation 5.3g₁:** $x_1 = 1\ \frac{W}{kg}$
- **Equation 5.3g₂:** $x_2 = 2\ \frac{W}{kg}$

Taking all participants into consideration, the load at the end of the exercise shows a mean reduction of 15% compared to P_{target}. This leads to the conclusion that P_{target} is probably inducing an HR above $HR_{training}$. Therefore, $P_{target\_estimated}$ needs to be reduced beyond the given 10% used in this study. In future studies we propose an additional decrease of 15% leading to a reduction of 23.5% of $P_{target\_estimated}$. Equation 5.6 is adjusted accordingly to equation 5.6b:

- **Equation 5.6b:** $P_{target} = P_{target\_estimated} * 0.765$

These calculations need to be verified.

Furthermore, the level of the current load needs to be considered in the ALC. The HR responds differently to a rise of 10 W depending on initial value, for example, 60 W compared to 200 W. We propose an adaptation of 20 W if the current Load ≧ 150 W. Additionally, the following time steps for load adaptation are specified:

- Load increase: following adaptation step after 60 sec
- Load decrease: following adaptation step after 30 sec

This schedule allows a faster response to an overpassing HR, while more time is allowed for an HR response below the $HR_{training}$.

In further studies the slope of the HR response curve additionally needs to be considered to improve the control of HR and the strain of the participants. One possible way is to approximate the HR response curve by an individually fitted exponential function (Bunc, Heller, & Leso, 1988).

Motivation of the participants

All participants reported to have fun playing the game and work out. In addition, the results of the kids-GEQ confirm the conclusion that the game “LetterBird” had a substantial short-term motivating effect on the participants. However, the effect of multiple training sessions needs to be further investigated. On the one hand, in this study a good reliability of the data was found only for the dimensions of competence and immersion. On the other hand, these reliabilities are higher compared to the studies of Poels et al. (kids-GEQ; Poels et al., 2008) and Nacke (GEQ; Nacke, 2009). Only the study of Poels, Kort, & IJsselstein (2009, GEQ) showed constantly high reliabilities in all dimensions of the GEQ, whereas all other reliabilities are inconsistent depending on the analyzed game and game settings.

Practical applications

The implementation of an algorithm for controlling the individual HR response to strain has a wide field of application. Typically, endurance intervention or training is controlled by HR. However, the delayed HR response reduces the effectiveness of those interventions. The presented algorithm has the ability to increase the effectiveness of all forms of cardio training including cardio exergames and other interventions in prevention, rehabilitation or health care.

5.6. Conclusion

The presented algorithm included in the "LetterBird" game turned out to be a reasonable link between adaptive training and a motivating serious game. It therefore appears to be a feasible method for controlling HR. However, the algorithm requires refinement and further research is needed to provide an effective and efficient tool for individual and adaptive training without overstraining the particular participant.

5.7. Acknowledgments

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5.8. Author Disclosure

The authors confirm that there are no financial or other conflicts.

5.9. References

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6. Manuscript III: Prediction and control of the individual Heart Rate response in Exergames

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Katrin Hoffmann is the main and corresponding author of this article responsible for the conception and design of the study and writing of the manuscript. Josef Wiemeyer was the supervisor of the project and contributed in discussions regarding interpretation of the results and writing the paper. Sandro Hardy was responsible for the development of the applied Exergames LetterBird.

6.1. Abstract

Setting an appropriate training load is one of the key elements for the success of exergames. Especially for the cardiovascular training, the adaptation of the current training load in accordance to an individually predetermined target training load plays an important role. In this paper, a new approach for the estimation and prediction of an individual's heart rate based on a monoexponential formula is presented and evaluated using statistical data. The estimation and prediction of the heart rate is a key factor for the calculation of adequate exertion parameters and therefore for the adaptation and personalization of exertion games, i.e. games that use whole-body exercises for game control. The tests reveal that the course of the heart rate response to changes of load bouts is not stable. Only a differential influence of gender on the HR course depending on the particular load bout can be found.

6.2. Introduction

In the physical training process, the appropriate strain of the human body is important to elicit optimal adaptations. However, the same defined external load can lead to different strain in different organisms. This individual response of the organism depends on a variety of factors, e.g., age, gender, BMI (i.e., ratio of body weight, and squared body height), fitness level, training biography and training goals. The response can be measured in various systems, e.g., the cardiovascular system (heart rate, blood pressure), the respiratory system (oxygen uptake), the metabolic system (lactate, ammonia), the hormonal system (cortisol, IGF-I), the immune system (leucocytes), or the autonomous system (adrenaline). An easy to measure indicator of the individual cardiovascular strain is the response of heart rate (HR in beats per minute, bpm) to the change of load bouts. In the sub maximal range, two characteristics of HR are important for estimating individual strain:

(a) The immediate short-term dynamics of HR after the onset of exercise or change of training load.

(b) The relation of HR and different training loads when HR has reached a steady state.

Bunc, Heller, & Leso (1988) described the course of this response by an exponential equation:

- **Equation 6.1:** $HR = a - b \cdot e^{-c \cdot t}$

Legend:

a	steady state HR level elicited by the change of load (HR_{steady} in Figure 6.1)
b	HR reserve, i.e., difference between a and the HR at the start of exercise
c	slope of HR curve
t	time [min]

Figure 6.1 illustrates the formula by means of a prototypical HR response.

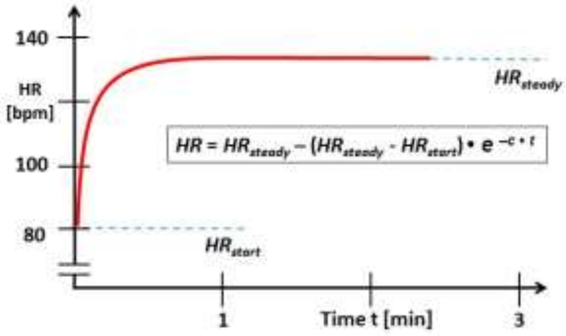

Figure 6.1 Illustration of the time course of HR according to the Bunc equation (Bunc et al., 1988).

The issue of adequate strain is also relevant for the application of Exergames to aerobic training. These games measure a player's bodily movement with sensor technology and use this information to control a video game. Such games have the potential to be used as efficient and effective tool to enhance physical fitness, at least at low fitness levels (Wiemeyer & Kliem, 2012). So, it is important to provide proper training stimuli for those games to ensure training efficiency. In Exergames, the additional difficulty arises that control of training strain may interfere with game control. Taking the example of a competitive running game, the player may increase pace to overtake an opponent which may result in a HR that is too high for optimal adaptations.

The purpose of the study was to test the feasibility of the Bunc equation within an Exergame. In particular, the use of the equation for predicting and controlling current strain is evaluated. On that account, different parameters of the formula are tested with HR data that was obtained by measuring the HR response while participants were playing the Exergame "Letterbird" (Hardy, Dutz, Wiemeyer, Göbel & Steinmetz, 2014; Hardy, Göbel, Gutjahr, Wiemeyer, & Steinmetz, 2011). This Exergame is based on the Exergame technology platform "StoryTecRT" (Hardy, Göbel, & Steinmetz, 2013). Using a bike ergometer as input device, "LetterBird" aims at providing playful endurance training.

This paper addresses the following research questions:

1. Is the individual course of the HR response stable over different load conditions inside the Exergame "LetterBird"?
2. Can this individual response be described and predicted by selected individual influencing factors?

6.3. Methods

6.3.1. Participants

HR data of 16 healthy and active participants (9 men, 7 female, age: M = 26.6 yr., SD = 4.45, $Range$ = 20 – 51 yr.; BMI: M = 22.9, SD = 1.78, $Range$ = 19.8 – 26.9) at the change of load bouts was used for the calculations. All participants reported to practice sport for at least 1.5 hours per week and to be active in their leisure time. 15 participants worked out more than 3 hours per week. 13 of 16 participants are members in a sports club. Demographic and anthropometric data is illustrated in Table 6.1.

Table 6.1 Demographic and anthropometric description of the participants – Manuscript III.

	Males (n=9)			Females (n=7)			Total (n=16)		
	M	**SD**	**Range**	**M**	**SD**	**Range**	**M**	**SD**	**Range**
Age [yrs]	26.56	4.45	13.00	33.43	10.49	31.00	29.56	8.18	31.00
Height [m]	1.84	0.06	0.21	1.73	0.06	0.15	1.80	0.09	0.28
Weight [kg]	81.11	7.10	20.00	65.00	5.72	18.00	74.06	10.40	38.00
BMI [kg/m2]	23.70	1.67	5.20	21.81	1.37	4.20	22.88	1.78	7.10

6.3.2. Apparatus

All tests were performed on a cycle ergometer with a flywheel (Daum Ergometer TRS 3, Germany). The HR was monitored by a chest belt (Polar T31, Finland) and processed by the ergometer. This data was saved together with a corresponding time stamp, the load (P in Watt, W) and the pedal rate (in revolutions per minute, rpm). The ergometer was connected to a computer where the exergame “Letterbird” was running.

The goal of the exergame “LetterBird” is to collect letters that are approaching a pigeon in different altitudes. By varying cadence, the player controls the flight altitude of the pigeon: If the player pedals faster the pigeon rises, whereas the pigeon sinks down at lower pedal rates.

In this test, the game control was set to control the pigeon within a range of 60 rpm to 80 rpm. The pigeon was flying at the bottom of the screen at 60 rpm and on top of the screen at 80 rpm. An increase or decrease beyond this range did not influence the gameplay. According to Löllgen, Graham, & Sjogaard (1980), this variance of pedal rate was expected to have no significant influence on HR.

The individual HR response of the participant was measured in a study for evoking an individually optimal training HR ($HR_{training}$). Therefore, the HR was obtained in two phases: the calibration and the exercise phase (see Figure 6.2; Hoffmann, Wiemeyer, Hardy, & Göbel, 2014).

In the calibration phase, the individual HR response to two defined, successive load levels (two minutes each) was measured while the participants were playing the Exergame “LetterBird”. The load was set depending on the body weight (in kg) of the participant:

- **Equation 6.2: load level 1 (P_{level1}) with P_{level1} = 1 W/kg * body weight**
- **Equation 6.3: load level 2 (P_{level2}) with $P_{level2v}$= 2 W/kg * body weight**

The obtained HR data was used to calculate a target load (P_{target}) that is expected to elicit $HR_{training}$.

A short break after the calibration phase allowed the HR to return to the resting level before starting the exercise phase. The first four minutes of the exercise phase replicated the calibration phase to validate the data obtained. This time schedule was determined as standard procedure. If P_{2level} in calibration phase was considerably higher than P_{target}, the strain on the participant likely exceeded the sub maximal range. Therefore, P_{2level} in the exercise phase was reduced to P_{target} ensuring a HR response resulting in a steady state. This time schedule was determined as exception procedure. Prototypical HR courses for each procedure are displayed in Figure 6.2.

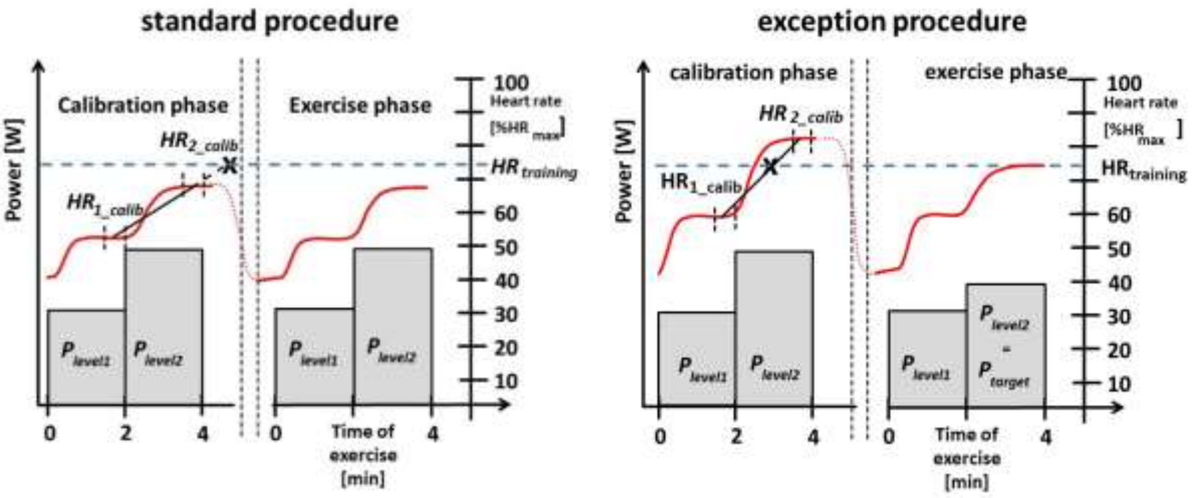

Figure 6.2 Prototypical HR courses during the first 4 minutes of the calibration and exercise phase of the study. Left side: standard procedure, right side: exception procedure; solid line: measured HR, dashed line: $HR_{training}$; HR_{1_calib}/ HR_{2_calib}: last 30 sec of each load level used for calculation (Hoffmann et al., 2014).

6.3.3. Procedure

Examination of HR data.
In this study, the first four minutes of each procedure were examined resulting in four load conditions:

- P_{level1} in the calibration phase: P_{level1_calib}
- P_{level2} in the calibration phase: P_{level2_calib}
- P_{level1} in the exercise phase: P_{level1_exer}
- P_{level2} (standard procedure)/P_{target} (exception procedure) in the exercise phase: P_{level2_exer}

For every load bout, the measured HR was approximated using the Bunc equation. On that account, the data was first normalized. Parameters a and b were directly estimated from the individual HR data with a represented by the steady state HR elicited by the change of load and b represented by the difference between mean HR at the end of the load level and initial HR. Parameter c was estimated using the linear regression analysis.

Two load conditions were excluded from further calculation due to a negative c value. In one case, this negative value was caused by a measuring error and in the other case by a load reduction. This leads to a total number of 62 load conditions:

- 16 conditions in P_{level1_calib}
- 16 conditions in P_{level2_calib}
- 15 conditions in P_{level1_exer}
- 15 conditions in P_{level2_exer}

Six participants performed the standard procedure, whereas 10 participants performed the exception procedure.

Stability test.
The stability of the parameter c over the different load conditions was tested by calculating Pearson correlation coefficients:

1. Stability between phases (within load levels):

   (a) correlation of $c\_P_{level1\_calib}$ and $c\_P_{level1\_exer}$
   (b) correlation of $c\_P_{level2\_calib}$ and $c\_P_{level2\_exer}$

2. Stability between load conditions (P_{level1} and P_{level2}):

   (a) correlation of $c\_P_{level1\_calib}$ and $c\_P_{level2\_calib}$ (calibration phase)
   (b) correlation of $c\_P_{level1\_exer}$ and $c\_P_{level2\_exer}$ (exercise phase)

Factors influencing c.
Factors influencing c were analyzed using different statistical methods. Age (in years), body weight (in kg) and physical activity (in hours per week) were correlated to the c values of all four load levels. Additionally, influences of gender were examined using a 2 (gender/activity level) x 2 (phase) x 2 (load level) ANOVA with repeated measures.

6.4. Results

6.4.1. Stability test

The stability test of the parameter c revealed unsatisfactory reliability (see Table 6.2). At equal load levels the correlations ranged from -.08 to .34. No correlation was significant.

Table 6.2 Retest reliability of c for different load levels (P_{level1} and P_{level2}), phases (calib – calibration and exer – exercise), and procedures.

Correlation	Total	Standard procedure	Exception procedure
1. (a) $c\_P_{level1\_calib}$ - $c\_P_{level1\_exer}$	.34		
1. (b) $c\_P_{level2\_calib}$ - $c\_P_{level2\_exer}$	.12	.30	-.08
2. (a) $c\_P_{level1\_calib}$ - $c\_P_{level2\_calib}$	-.36		
2. (b) $c\_P_{level1\_exer}$ - $c\_P_{level2\_exer}$	-.41	-.59	-.44

6.4.2. Factors influencing c

The influence of body weight on c was inconsistent and small (see Table 6.3). Only one correlation was significant. Body weight was correlated significantly positive with $c\_P_{level2\_calib}$. This means that the higher the body weight the steeper the HR rises at load level 2.

The influence of age was also inconsistent and small (see Table 6.4). None of the correlations were significant.

No significant correlations were found between physical activity level and c (see Table 6.5).

Table 6.3 Correlation between body weight (BW) and c for different load levels (P_{level1} and P_{level2}), phases (calib – calibration and exer – exercise), and procedures.

Correlation	Total	Standard procedure	Exception procedure
BW – $c\_P_{level1\_calib}$	-.380		
BW – $c\_P_{level1\_exer}$	-.360		
BW – $c\_P_{level2\_calib}$	.548 *		
BW – $c\_P_{level2\_exer}$	.042	.232	-.060

* 2p < .05

Table 6.4 Correlation between age and c for different load levels (P_{level1} and P_{level2}), phases (calib – calibration and exer – exercise), and procedures.

Correlation	Total	Standard procedure	Exception procedure
Age – $c\_P_{level1\_calib}$	.396		
Age – $c\_P_{level1\_exer}$	.202		
Age – $c\_P_{level2\_calib}$	-.179		
Age – $c\_P_{level2\_exer}$	-.277	-.382	-.291

Table 6.5 Correlation between physical activity level (PAL; hours per week) and c for different load levels (P_{level1} and P_{level2}), phases (calib – calibration and exer – exercise), and procedures.

	Total	Standard procedure	Exception procedure
PAL – $c\_P_{level1\_calib}$	.081		
PAL – $c\_P_{level1\_exer}$	-.241		
PAL – $c\_P_{level2\_calib}$	.268		
PAL – $c\_P_{level2\_exer}$	-.083	-.586	.307

Gender differences are illustrated in Figure 6.3. 2x2x2 ANOVA with repeated measures revealed a significant two way interaction of gender and load level ($F1, 12 = 5.17$, $p<.05$, $\eta 2part = 0.301$). No main effects or further interactions were significant.

According to Figure 6.3, males had significantly lower c values at P_{Level1} both in the calibration phase (*U test:* $z = -1.75$, $p<.05$) and in the exercise phase (*U test:* $z = -2.03$, $p<.05$), whereas females had significantly lower c values at P_{Level2} in the calibration phase (*U test:* $z = -2.23$, $p<.05$).

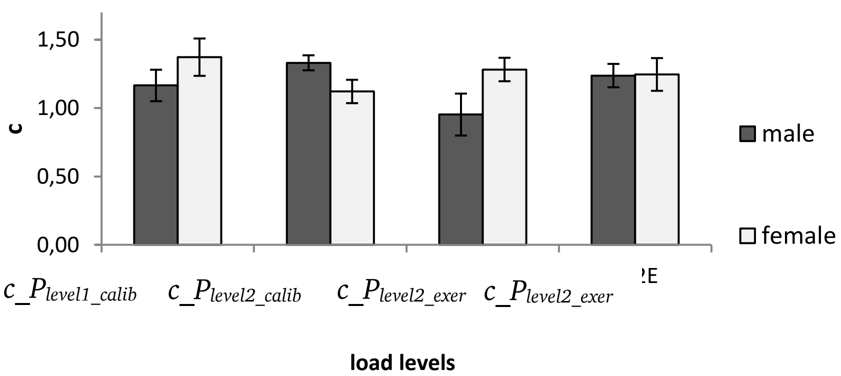

Figure 6.3 Comparison of mean c value for men and women in the corresponding load levels.

6.5. Discussion

The non-significant correlations in the stability tests revealed that the c values are highly dependent on the particular load level and phase. This leads to the conclusion that the isolated c value is not useful to predict HR courses in the Exergame "Letterbird". Further differentiation of the participants is needed.

On that account, the influences of age, gender, body weight, and activity level were tested for all load changes. The data revealed that there are no consistent correlations between age, body weight, and activity level and the c values. There was only one significant correlation between body weight and $c\_P_{level2\_calib}$. All other correlations were not significant. Concerning body weight and age, correlations even changed sign.

Gender was a factor discriminating among c values. However, the significant interaction of gender and load level revealed a slower HR increase in males at the lower load level (irrespective of phase), whereas HR increase was steeper in males at the higher load level in the calibration phase.

The following statements for a prediction of the HR response to defined load changes can be made using the present data:

- The increase of HR at the onset of exercise and change of load is not stable over different load conditions inside the Exergame "LetterBird".
- Age, body weight, and activity level cannot be used as indicators for predicting the HR course.
- Gender differences have to be considered depending on load level.

A possible reason for the lack of stability of c is the influence of pedal rate on HR. Due to motivating factors, the participants exceeded the pedal rate beyond the given range to control the game. This became especially apparent when the controlled pigeon was located far apart from the collectable letter. A more promising factor for individual load control may be the performance level of the participants.

Furthermore, the sample size in this study is very small and effects need to be retested using a bigger sample size. Additionally, the effect of age needs to be tested in a wider range, as the sample is not covering the whole range of age (*range*: 20 – 51years). Particularly in adults, the increase of HR should be steeper compared to children (e.g., Cooper, Berry, Lamarra, & Wassermann, 2014; Springer, Barstow, Wassermann, & Cooper, 1991).

In future studies, more sophisticated approximation algorithms (i.e. PerPot (Perl, 2001) for predicting the HR course need to be considered.

6.6. Conclusion

A prediction of HR within the Exergame "LetterBird" using solely the Bunc equation is considered difficult as the slope of HR was not stable at different load levels and phases. Further tests revealed only a differential influence of gender depending on the particular load level.

6.7. Acknowledgements

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7. Manuscript IV: Statistical Models for Predicting Short-Term HR Responses to Submaximal Interval Exercise

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7.1. Abstract

Aim of the study was to identify possible predictors influencing the variability of individual short-term heart rate (HR) responses to submaximal interval exercise using a probabilistic model. Short-term HR responses to the change of load bouts obtained in a twelve-week training intervention were analyzed. Questionnaires gathered preceding sport activity, sleep, nutrition, health and mood prior to each training session. Additionally, time of the day and number of interval was included in calculation. Multiple regression method was used to identify predictors for start heart rate, steady state HR, and for the slope of the HR curve. Especially the number of the interval, physical and mental health, and negative mood were influencing these responses. The start heart rate was identified as predictor in five of eight response parameter. Time was a factor highly varying between participants. Future research need to validate the results in a wider sample and integrate more parameters in the analysis.

Keywords: short-term HR responses, modeling, individual.

7.2. Introduction

All over the world, the level of physical inactivity is rising (WHO, 2010) although the positive influence of physical activity on health has been empirically verified and widely propagated. However, significant changes on health require an individually optimized training to induce the desired positive effects. As insufficient load may result in suboptimal or missing adaptations, overload may cause risks like injuries.

In endurance training, the heart rate (HR) is considered a valid and valid indicator for measuring individual strain. HR is a non-invasive and instant marker and the measurement does not interfere with the trainee’s movements.

For optimal adaptations, the individual optimal strain needs to be evoked in the training person. However, predicting this optimal strain is challenging as identical load can induce completely different responses in different individuals. These responses depend on a high variety of influencing factors, e.g., age, gender, or training status (Hoffmann, Wiemeyer, & Hardy, 2016). In order to enable an immediate adjustment of induced load, the individual responses have to be modeled and predicted during or prior to training.

Numerous studies can be found focusing on modeling individual strain (Ludwig, Sundaram, Füller, Asteroth, & Prassler, 2015). Most models require the estimation of individual parameters derived from the training data to fit the model individually to the subject. In general, the parameters characterize time constants (Engelen et al., 1996) as well as constant or varying model parameters (Baig, 2014; Stirling, Zakynthinaki, Refoyo, & Sampredo, 2008). Machine learning approaches such as artificial networks (Xiao, Chen, Yuchi, Ding, & Jo, 2010) require a data set for learning. Whereas some authors integrate time varying parameters (Baig, 2014; Cheng et al., 2008) expecting an increase of HR over the training time, most models predict individual HR presupposing similar or equal levels at a given stress. The HR response to the change of load bouts is a varying signal that seems to be additionally influenced by rather temporarily and fluctuating factors. Several studies show an influence of current psychophysical states of the individual HR. Detailed analyses of multiple factors influencing short-term HR response in different individuals are (still) missing.

The aim of this paper is to identify the influence of temporary factors on HR and develop individual probabilistic prediction models. Therefore, HR data obtained in a 12-week endurance training intervention on a bike ergometer was analyzed. Based on literature analysis, questionnaires were used to gather information about the psychophysical state of the individual.

7.3. Material and Methods

The study presented here was approved by the Ethics Committee of the Technical University of Darmstadt in 2016.

7.3.1. Participants and Apparatus

Four healthy and active adults volunteered to participate in the study after having signed an informed consent. The participants' characteristics are displayed in Table 7.1.

Table 7.1 Demographic and anthropometric description of the participants – Manuscript IV.

	Participant 1 (P1)	Participant 2 (P2)	Participant 3 (P3)	Participant 4 (P4)
Age [years]	31	32	32	31
Height [m]	168	175	182	185
Weight [kg]	79.2	69.5	88.2	96.1
Sex	Female	Female	Male	Male
BMI [kg/m²]	28.1	23.0	26.7	27.6
Activity time per	3.5	2	7	3

All tests were performed using a cycle ergometer with a flywheel (Daum Ergometer 8008 TRS 3; Fürth, Germany). The power was controlled by the resistance at the flywheel and measured in Watts by the ergometer. HR data was successively recorded beat by beat using a Polar V800 sport watch (Polar Electro, Kempele, Finnland) and a corresponding Polar chest belt (T31). Data recording started at the beginning of the training protocol. Respiratory parameters were recorded using the spiroergometry device K5 (COSMED, Rome, Italy) during the exhaustion and the sub tests using a mixing chamber. First anaerobic threshold (VT_1) and second anaerobic threshold (VT_2) were automatically calculated from the respiratory parameters using the OMNIA Software (COSMED, Rome, Italy).

7.3.2. Protocol

All data was obtained during a twelve-week endurance training intervention on a bike ergometer. This duration was chosen as adaptations to the training can be reliably observed after this training period (Blank, 2007). Prior to and after completion of the intervention, the participants performed an all-out exhaustion test to estimate the individual maximal HR (HR_{max}), maximal Oxygen Uptake (VO_{2max}) and the individual anaerobic thresholds of the participants. Additionally, two subtests were performed in week 4 and 8 to adapt the training intensity to the training status of the participants during the training process.

The protocol of the exhaustion test started with a resting period with the participants sitting still on the ergometer. After 3 min, the participants started pedaling for 2 min at 25 W, followed by 3 min at 50 W. After this warm-up period, the load at the ergometer was successively increased by 50 W every 3 minutes until exhaustion. In the subtests, the warm-up period of the exhaustion tests was repeated. Subsequently, the participants had to pass an exercise phase of three increasing load levels for three minutes each. The load for these load levels was calculated to induce responses corresponding to the individual's anaerobic thresholds. Therefore, the first load was calculated to evoke responses below VT_1, the second load was calculated to evoke responses between VT_1 and VT_2 and the third load was calculated to evoke responses above VT_2. After this 9 min exercise period, a resting period of 5 min active recovery at 25 W was applied. Subsequently, another 9 min exercise phase and 5 min recovery phase were successively added to validate the results.

According to the guidelines of the WHO (WHO, 2006) the training volume for the intervention was set to 25 min of intensive training three times a week. Three different training methods were applied: the intensive continuous method (*ICM*), the extensive interval method (*EIM*) and the intensive interval method (*IIM*) (Hohmann, Lames, & Letzelter, 2002). The load for each protocol was calculated to evoke the target HR ($HR_{training}$) using the HR responses and the corresponding load levels from the first exhaustion test and the subtests. The training protocols are displayed in Table 7.2 in detail.

Table 7.2 Protocols for the training intervention – Manuscript IV.

	Intensive Endurance Method (*ICM*)	Extensive Interval Method (*EIM*)	Intensive Interval Method (*IIM*)
Intensity	75% HR_{max}	80% HR_{max}	95%HR_{max}
Load period	25 min	3:30 min	1:00 min
Recovery Time between load intervals	0 min	1:30 min	1:30 min
Repetitions	1	5	10

All protocols were automatically applied at the ergometer. The participants were advised to keep the pedal rate (PR) constant at 80 revolutions per minutes (RPM; Coast, Cox & Welch, 1986).

7.3.3. Data Processing

HR data for the exercise phases of the *EIM* training protocol was analyzed. In this training protocols, the HR of the participant is expected to stay constant within a submaximal range. Therefore, short term HR responses to the change of load bouts are expected to increase linearly in the beginning, followed by an exponential increase into a steady state. Steady state is reached when the variation of HR does not exceed a corridor of 5 bpm for the rest of the exercise interval (Kamath, Fallen & McElvie, 1991). The time of the load phases in the *EIM* is expected to be sufficient that HR can reach this steady state.

HR data of the participants was automatically divided into exercise and recovery phases for each training protocol. The phases started with the change of the load at the ergometer. The warm-up period and the recovery phases were not part of the computations. Thus, we obtained 60 HR curves for each participant.

In a first step, specific values of each HR response were calculated. HR_{start} was calculated as minimum HR value in the first 10 s of each curve to compensate possible measuring errors caused by the variability of HR. The mean HR over the last 30 s of each curve was calculated as HR_{steady} for all given data. In total, 240 data sets were processed for calculating HR_{start} and HR_{steady}.

Additionally, the slope of each curve (c) was approximated using the monoexponential formula proposed by Bunc, Heller, & Leso (1988) (see Figure 7.1). According to Bunc et al. (1988), the submaximal HR response to the change of load bouts is described by the following equation:

- **Equation 7.1:** $\boldsymbol{HR = a - b \cdot e^{-c \cdot t}}$ (Bunc et al., 1988)

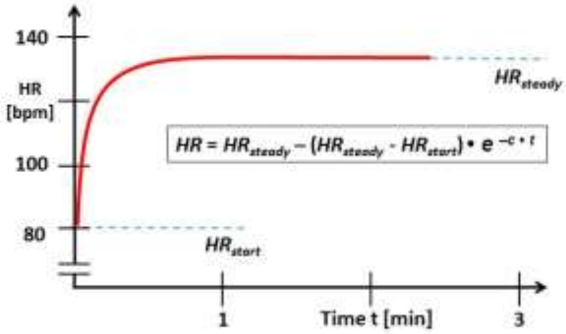

Figure 7.1 Prototypical time course of HR according to the Bunc equation (Bunc et al., 1988).

Legend:
a – steady state HR level elicited by the change of load (HR_{steady}) [bpm]
b – deviation of HR_{steady} and HR at the start of exercise (HR_{start}) [bpm]
c - slope of HR curve
t - time [min]

For approximation, parameters a and b representing HR_{steady} and the deviation of HR_{steady} and HR_{start} were directly estimated from the data. Subsequently, the HR data was linearized and parameter c was estimated using the linear regression analysis. Due to incomplete HR courses caused by measuring errors, six curves were excluded for calculating value c. In total, 234 data sets were processed calculating value c.

7.3.4. Recording of influencing factors

Prior to the training, the participants completed questionnaires to identify possible influencing factors. The first questionnaire was a self-developed instrument based on literature reporting factors that might influence HR responses. Sport activity 24 hours prior to the training was recorded regarding type, duration, and intensity. Additionally, the participants declared if they felt any pain, soreness or fatigue induced by this prior sport activity (*Interf*). The restfulness of the sleep (Ewing, Neilson, Shapiro, Stewart, & Reid, 1991) in the night prior to the training was assessed with a five point Likert scale (1: very restful, 5: not at all restful). The nutrition two hours before the training (Heseltine, Potter, Hartley, Macdonald, & James, 1990) was assessed by a three point scale ("1" - nothing, "2" - light meal, "3" - full meal). The current health status (WHO, 2006) was measured by three items regarding physical health, psychic health and social health on a 5 point scale ranging from 1 "very bad" to 5 "very high".

The influence of mood on the HR and the HR response has been widely verified (Broschot, & Thayer, 2003). Therefore, the current mood of the participants was measured with the "Stimmungs- und Befindens-Skalen" (Trait and State of Mood Skale, SBS; Hackfort, &

Schlattmann, 1995). The SBS consists of 8 items regarding "Activation", "Contact Motivation", "Self Confidence", "Cheerfulness", "Nervousness", "Sleepiness", "Irritability", and "Dejectedness". Whereas the first four items have a positive valence, the last four items have a negative valence. Each item is described by three words each (e.g., "Self Confidence": confident, ascendant, experienced). All items are scored on a Likert Scale ranging from 0 (not applicable) to 10 (fully applicable). Additionally, the time of the day and the number of the interval was included in the analysis.

In total, 19 variables were measured. To integrate only variables that are independent of each other, some variables were grouped together. The type, duration and intensity of the prior sport activity was converted into the metabolic equivalent (*MET*) according to widely accepted compendium (Ainsworth et al., 2011). Mood was aggregated in positive mood (*SBS+*) and negative mood (*SBS-*). The mean value of the four corresponding items was used for calculation.

The constant parameters age, gender, and training status were excluded from calculation. Additionally, the load applied at the ergometer was also excluded from calculation as this load was expected to evoke a reproducible constant HR response to the defined target HR.

In total, 11 predictors were integrated in the analysis. Figure 7.2 displays the workflow.

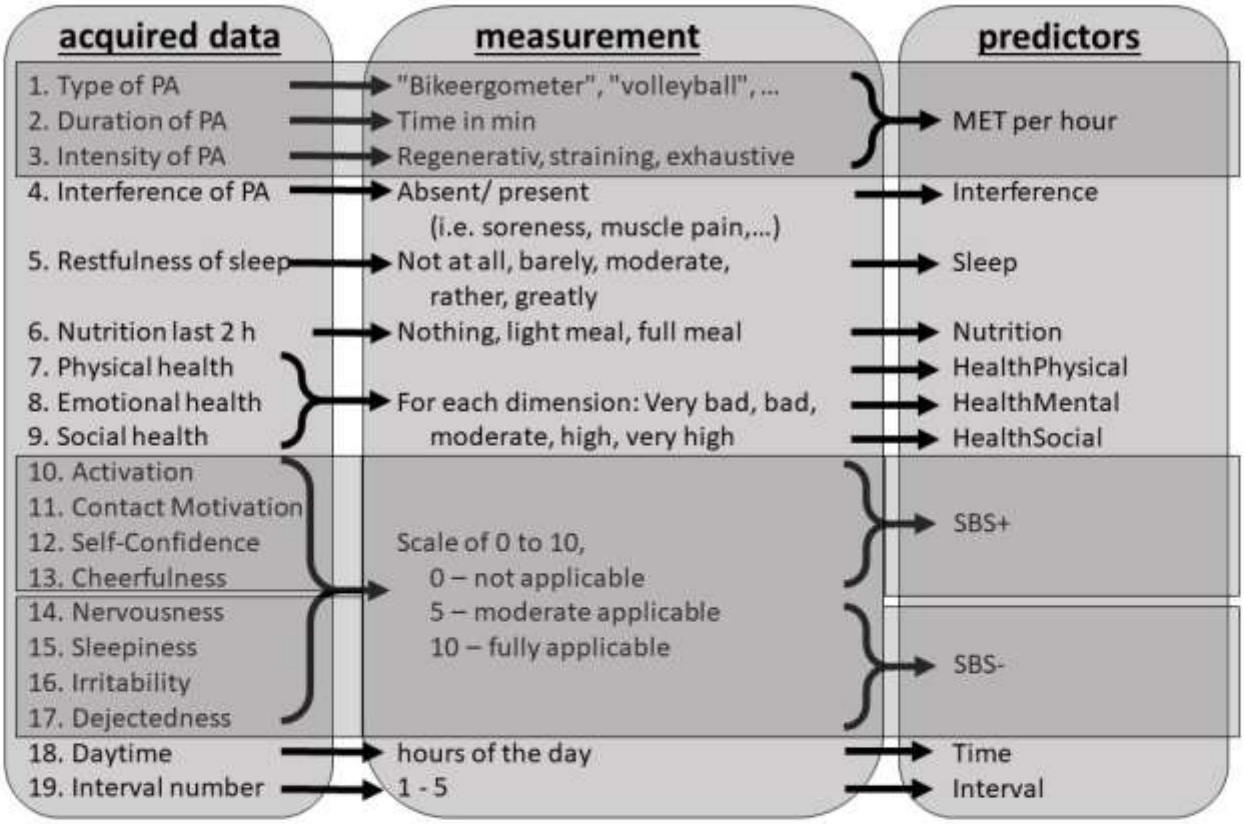

Figure 7.2 Process of data acquisition, aggregation and predictors; PA: physical activity.

7.3.5. Statistical analysis

All statistical analyses were performed with IBM SPSS Statistics 24.

In order to confirm submaximal strain in all participants, we tested if steady state was reached in all HR curves. HR was preprocessed using the moving average method. Steady state was reached when the difference of the measured HR and HR_{steady} was smaller than 5 bpm and the increase of the averaged HR was smaller than 5 bpm. The deviation of HR_{steady} from the $HR_{training}$ was calculated for each participant to identify a varying response in each participant.

Multiple regression methods were used to evaluate the overall contribution of the influencing factors on the dependent variables HR_{start}, HR_{steady}, and c. As HR adaptations and perception of trait is very individual the tests were performed for each participant. At first, a regression model with stepwise integration was applied to identify significant influencing factors. Durbin-Watson values were calculated to indicate an absence of autocorrelation of the dependent values. Additionally, another stepwise multiple regression was calculated for HR_{steady}, and c integrating HR_{start} as possible influencing factor. This method was chosen after examining the raw HR data to analyze the prediction feasibility of HR_{start}. Factors that were retained in the stepwise model were then analyzed with a multiple regression model using forward selection.

7.4. Results

Steady State was reached in all HR curves (*Mean* = 117.5 sec, *SD* = 25.8 sec, *Max* = 190 sec, *Min* = 48 sec). In all participants, HR_{start} and HR_{steady} increased during the training session. The highest increase was found in participant 4 (see Table 7.3). No difference of HR_{start} or HR_{steady} were observed depending on the week of the training. Statistical data of HR_{start} and HR_{steady} for all exercise phases is displayed in Table 7.3.

Table 7.3 HR_{start} and HR_{steady} for all participants.

	Participant 1		Participant 2		Participant 3		Participant4	
	HR_{start}	HR_{steady}	HR_{start}	HR_{steady}	HR_{start}	HR_{steady}	HR_{start}	HR_{steady}
Mean	118.7	148.0	108.4	147.9	97.8	144.9	106.7	146.3
SD	8.86	8.75	7.84	4.57	7.91	7.53	11.16	7.98
Max	140	168	123	156	119	165	135	168
Min	97	132	82	131	81	128	86	127

In all participants a high variation of the deviation of HR_{steady} from $HR_{training}$ was observed (*Mean* = 3.83, *SD*=7.28, *Min*= -14 bpm, *Max* = 27 bpm). The lowest mean deviation was found in participant 2 (*Mean* = 0.08 bpm, *SD* = 4.56 bpm, *Min* = -8 bpm, *Max* = 17 bpm).

The multiple regression method revealed significant predictors for all values except for c in participant 1, participant 3 and participant 4. If HR_{start} was included in calculation, predictors for all values were found. All displayed predictors met the requirements for applying the regression method. The Durbin-Watson values varied but showed a higher acceptability only in participant 2 if HR_{start} was included. Only the values for HR_{steady} in participant 2 and 3 require further attention. If the multiple regression did not reveal any predictors, no values were calculated. All Durbin-Watson values are displayed in Table 7.4.

Table 7.4 Durbin-Watson test for all calculated regressions.

	Participant 1		Participant 2		Participant 3		Participant 4	
	-	+	-	+	-	+	-	+
HR_{start}	1.955	x	1.792	x	1.680	x	1.636	x
HR_{steady}	2.100	1.812	1.206	1.384	1.682	1.137	2.183	2.183
c	x	1.627	2.009	2.009	x	2.064	x	1.866

Legend:
- : HR_{start} was not included in calculation
+: HR_{start} was included in calculation
x: no Durbin-Watson-Value calculated

7.4.1. Participant 1

The responses HR_{start} and HR_{steady} of participant 1 showed a high influence of multiple predictors. If HR_{start} is not included in calculation no predictors were identified for value c. Time of the day and nutrition were predictors that were found in all HR values. HR_{start} was a main predictor for HR_{steady} and the only predictor for value c. All data is displayed in Table 7.5.

Table 7.5 Revealed predictors in participant 1, left side: results for predictors without inclusion of HR_{start} in calculation, right side: results for inclusion of HR_{start} in calculation.

HR_{start}							
	R^2	F	Sig.		R^2	F	Sig.
HealthMental	.201	15.80	.000				
Time	.329	15.433	.000				
SBS-	.558	25.84	.000				
Interval	.640	27.17	.000				
Sleep	.686	26.78	.000				
HealthPhysical	.730	27.55	.000				
SBS+	.793	33.24	.000				
Nutrition	.822	35.03	.000				
HR_{steady}				**HR_{steady}, with HR_{start} included**			
HealthMental	.256	21.28	.000	HR_{start}	.732	162.43	.000
Time	.396	18.71	.000	MET	.754	91.39	.000
SBS-	.647	34.16	.000	Time	.789	74.54	.000
Interval	.723	35.83	.000	Nutrition	.812	64.68	.000
MET	.783	39.00	.000				
HealthSocial	.856	52.59	.000				
Interference	.876	52.50	.000				
c				**c, with HR_{start} included**			
no variables found				HR_{start}	.091	6.92	.011

7.4.2. Participant 2

The responses in participant 2 also showed multiple predictors for the HR responses. Especially nutrition and physical health were predictors that were found in HR_{start} and HR_{steady}. The slope of the curve represented by value c was only influenced by the sport activity prior to the training and by possible interference effects. If HR_{start} was included as predictor, only HR_{start}, interval and the time of the day influenced HR_{steady}. No change was observed for value c. All data is displayed in Table 7.6.

Table 7.6 Revealed predictors in participant 2, left side: results for predictors without inclusion of HR_{start} in calculation, right side: results for inclusion of HR_{start} in calculation.

HR_{start}							
	R^2	F	Sig.		R^2	F	Sig.
Interval	.142	10.75	.002				
Nutrition	.269	11.85	.000				
HealthPhysical	.531	23.28	.000				
SBS+	.561	20.33	.000				
HealthMental	.654	23.34	.000				
HR_{steady}				**HR_{steady}, with HR_{start} included**			
Interval	.410	40.38	.002	HR_{start}	.497	57.39	.000
Nutrition	.475	25.75	.000	Interval	.653	53.52	.000
HealthPhysical	.576	25.35	.000	Time	.689	41.29	.000
SBS-	.699	31.90	.000				
Sleep	.747	31.90	.000				
c				**c, HR_{start} included**			
MET	.061	4.84	.032	MET	.061	4.84	.032
Interference	.195	6.92	.002	Interference	.195	6.92	.002

7.4.3. Participant 3

The main predictor for participant 3 was the number of the interval. No variables were found without inclusion of HR_{start} as predictor for value c. HR_{start} was the only predictor for HR_{steady} and c if included in the calculation. Although we received low Durbin-Watson values, the F test of the developed models show a high significance. All data is displayed in Table 7.7.

Table 7.7 Revealed predictors in participant 3, left side: results for predictors without inclusion of HR_{start} in calculation, right side: results for inclusion of HR_{start} in calculation.

HR_{start}							
	R^2	F	Sig.		R^2	F	Sig.
Interval	.368	33.80	.000				
MET	.588	40.61	.000				
SBS-	.724	48.90	.000				
HR_{steady}				***HR_{steady}, HR_{start}* included**			
Interval	.254	21.14	.000	*HR_{start}*	.583	83.59	.000
Interference	.371	18.37	.000				
HealthPhysical	.414	14.89	.000				
HealthSocial	.572	20.74	.000				
Nutrition	.701	28.72	.000				
c				***c*, *HR_{start}* included**			
No variables found				*HR_{start}*	.141	9.84	.003

7.4.4. Participant 4

The predictors of HR_{steady} and c in participant 4 were independent of inclusion of HR_{start}. Especially the number of interval explains 47% of the variance of HR_{start} and 42% of the variance of HR_{steady}. All data is displayed in Table 7.8.

Table 7.8 Revealed predictors in participant 4, left side: results for predictors without inclusion of HR_{start} in calculation, right side: results for inclusion of HR_{start} in calculation.

HR_{start}							
	R^2	F	Sig.		R^2	F	Sig.
Interval	.476	54.57	.000				
Time	.571	40.22	.000				
HR_{steady}				***HR_{steady}, HR_{start}* included**			
Interval	.424	44.40	.000	Interval	.424	44.40	.000
MET	.641	53.62	.000	MET	.641	53.62	.000
SBS-	.702	47.43	.000	SBS-	.702	47.43	.000
Sleep	.751	45.45	.000	Sleep	.751	45.45	.000
SBS+	.791	45.62	.000	SBS+	.791	45.62	.000
HealthPhysical	.834	50.50	.000	HealthPhysical	.834	50.50	.000
Time	.867	56.12	.000	Time	.867	56.12	.000
HealthSocial	.878	53.93	.000	HealthSocial	.878	53.93	.000
c				***c*, *HR_{start}* included**			
MET	.068	5.20	.026	MET	.068	5.20	.026
Time	.119	4.92	.011	Time	.119	4.92	.011
Interference	.209	6.12	.001	Interference	.209	6.12	.001

7.5. Discussion

The aim of the study was to identify individual predictors for short-term HR responses. All models including the proposed predictors the individual HR-responses show a high significance.

Especially, the number of the interval was a strong predictor that was found in all participants for HR_{start} and HR_{steady}. This corresponds to results found in other studies, that HR is increasing during interval training (Meyer et al., 1996). Interestingly, negative mood effected the HR responses more often than positive mood. The predictor was found especially in HR_{steady} except for P3. Additionally, physical health was found as strong predictor for HR_{steady}, except for P1. This might be caused by the participant´s health status. The participant stated only to be either moderately or highly physically healthy, whereas in the other participants a greater heterogeneity was observed. Additionally, mental health was a predictor for HR_{steady} in all participants except for P2. In general, the slope of the curve represented by value c revealed only weak predictors. The sport activity represented by MET and possible interference by previous sport activity explains as 19% of the variances of value c in participants 2 and 4.
Time of the day was a factor highly varying in the participants. It was revealed as predictor for HR_{start} and HR_{steady} in participant 1 and for all values in P4. In contrast, neither P2 nor P3 showed an influence of Time.

HR_{start} was found to be a strong predictor in most participants except for P4. Especially in P3, HR_{start} was the only predictor for HR_{steady} and the slope of the course. HR_{start} even explained 58% of the variability of HR_{steady} in this participant. No specific gender-related predictors were found. All predictors are summarized in Table 7.9.

With the present data, the developed models show a reasonable approach for modeling individual short-term HR responses. Especially HR_{start} requires further attention. Regarding the literature, inducing the optimal training strain requires only the application of the correct training load. This study shows that there are more influencing factors ranging from physiological to mental that also needs to be considered.

In future research, the influence of additional predictors (e.g., weather, temperature or drinking behavior) need to be further investigated. Additionally, the assessment of a physiological profile might be useful to further analyze the resilience of the individuals.

Table 7.9 Revealed predictors for all participants, HR_{start} was rated separately.

	Participant 1			Participant 2			Participant 3			Participant 4			sum
	HR_{start}	HR_{steady}	c	HR_{start}	HR_{steady}	c	HR_{start}	HR_{steady}	c	HR_{start}	HR_{steady}	c	
MET		x				x	x				x		4
Interf		x				x		x					3
Sleep	x				x						x		3
Nutr	x			x	x			x					4
HPhys	x			x	x			x			x		5
HMent	x	x		x									3
HSoc		x						x			x		3
SBS+	x			x							x		3
SBS-	x	x			x		x				x		5
Time	x	x								x	x	x	5
Interv	x	x		x	x		x	x		x	x		8
HR_{start}		x	x		x			x	x				5

7.6. Conclusion

In conclusion, possible predictors influencing the short-term HR responses are varying between individuals. Nevertheless, the number of interval, physical health, Time and negative mood are influencing these responses. The HR at the change of load bout is an important predictor even in the submaximal range. Future research needs to validate the results in a larger sample and integrate more parameters in the analysis.

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8. Manuscript V: Predicting Short-Term HR Response to Varying Training Loads Using Exponential Equations

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Katrin Hoffmann is the main and corresponding author of this article responsible for the conception and design of the study and writing of the manuscript. Josef Wiemeyer was the supervisor of the project and contributed in discussions regarding interpretation of the results and writing the paper.

8.1. Abstract

Aim of this study was to test whether a monoexponential formula is appropriate to analyze and predict individual responses to the change of load bouts online during training. Therefore, 234 heart rate (HR) data sets obtained from extensive interval protocols of four participants during a twelve-week training intervention on a bike ergometer were analyzed. First, HR for each interval was approximated using a monoexponential formula. HR at onset of exercise (HR_{start}), HR induced by load (HR_{steady}) and the slope of HR (c) were analyzed. Furthermore, a calculation routine incrementally predicted HR_{steady} using measured HR data after onset of exercise. Validity of original and approximated data sets were very high (r^2 =.962, *SD* =0.025; *Max* =0.991, *Min* =0.702). HR_{start} was significantly different between all participants (one exception). HR_{steady} was similar in all participants. Parameter c was independent from the duration of intervention and intervals regarding one training session but was significantly different in all participants (one exception). Final HR was correctly predicted on average after 58.8 s (*SD* = 34.77, *Max* =150 s, *Min* =30 s) based on a difference criteria of less than 5 bpm. In 3 participants, HR_{steady} was predicted correctly in 142 out of 175 courses (81.1%).

Keywords: adaptation, HR responses, monoexponential equation

8.2. Introduction

In the physical training process, optimal training adaptations require individually optimized strain on the human body. However, it is very challenging to apply individually optimal stress that induces the required strain without any prior knowledge of the factors influencing this individual response (e.g., training condition, fatigue caused by prior training load). Whereas an overestimated load might result in overstraining and potential risks for the athletes, insufficient load might result in ineffective training and minor or no adaptation to training. A fast and valid prediction of this individual strain is therefore essential for an optimal training regarding training effectiveness and efficiency as well as risk minimization, and time-optimization.

To identify the individual strain, the individual response to the change of load can be measured in various systems of the human body, for example, the cardiovascular system (e.g., heart rate, blood pressure), the cardiorespiratory system (e.g., oxygen uptake), the metabolic system (e.g., lactate, ammonia), the hormonal system (e.g., cortisol, IGF-I), the immune system (e.g., leucocytes), or the autonomous system (e.g., adrenaline). Especially in endurance training, the individual heart rate (HR in beats per minute, bpm) response has become a very important indicator to measure and determine responses representing individual strain of the human organism.

As identical load can induce completely different responses in different individuals, the prediction of individual strain is very challenging. Even in the same individual, a varying response can be observed depending on a variety of influencing factors, e.g., different environmental conditions, the current psychophysical state, muscle temperature or exhaustion of the cardio respiratory system (Hoffmann, Wiemeyer, & Hardy, 2015).

Another difficulty arises as the HR is not a fixed signal but is modulated by numerous influencing factors, e.g., the autonomous nervous system, arterial and cardiopulmonary baroreflexes or humoral mechanisms. Therefore, the HR shows considerable variability due to these influences (Sykrs, 1973).

Additionally, the short-term response of HR to the change of load bouts is delayed and seems to follow an exponential curve. When applying a submaximal exercise intensity, two physiologically different HR dynamics can be observed: the HR increases at the onset of exercise (HR_{start}) and the HR plateau corresponding to the applied load (HR_{steady}) representing the zone of steady state. If the load exceeds the submaximal range an additional upward drift of the HR can be observed (Åstrand & Rodahl, 1970).

In the literature, different formulas and procedures describing and modeling this individual HR response to the change of load bouts can be found (Ludwig, Sunduram, Füller, Asteroth, & Prassler, 2015). Besides analytical models such as exponential models (e.g., Bunc, Heller, & Leso, 1988), systems of linear equations (e.g., Le, Jaitner, Tobias, & Litz, 2008; Baig, 2014) and systems of non-linear equation (e.g., Cheng et al., 2008; Stirling, Zakynthinaki, Refoyo, & Sampredo, 2008), machine learning approaches such as artificial neuronal networks (e.g., Xiaro, Chen, Yuchi, Ding, & Jo, 2010; Sumida, Mizumoto, & Yasomoto, 2013) have been used for approximation.

The problem of most approaches is that calculation of steady state HR corresponding to the change of load requires the estimation of additional variables. These parameters mostly need to be estimated in additional tests prior to the training. Le et al. (2008), for example, presume that the individual anaerobic threshold is known; Stirling et al. (2008) require the individual maximal HR for calculation. Additionally, several procedures such as artificial neuronal networks (Xiaro et al., 2010) or machine learning approaches require a data set for learning the individual adaptation parameters.

To enable a calculation of HR without any additional knowledge, the Bunc formula was used as a straightforward method taking into account only the resting HR value and HR data obtained while training. This data was used for calculating the individual steady state HR and the individual slope of the adaptation course of HR. This formula describes the course of the HR response by the following equation:

- **Equation 8.1:** $\boldsymbol{HR = a - b \cdot e^{-c \cdot t}}$ (Bunc et al., 1988)

Legend:
a - steady state HR level elicited by the change of load (HR_{steady} in Figure 8.1)
b - HR reserve, i.e., difference between HR_{steady} and the HR at the start of exercise (HR_{start})
c - slope of HR curve
t - time [min]

Figure 8.1 illustrates the formula by means of prototypical HR responses.

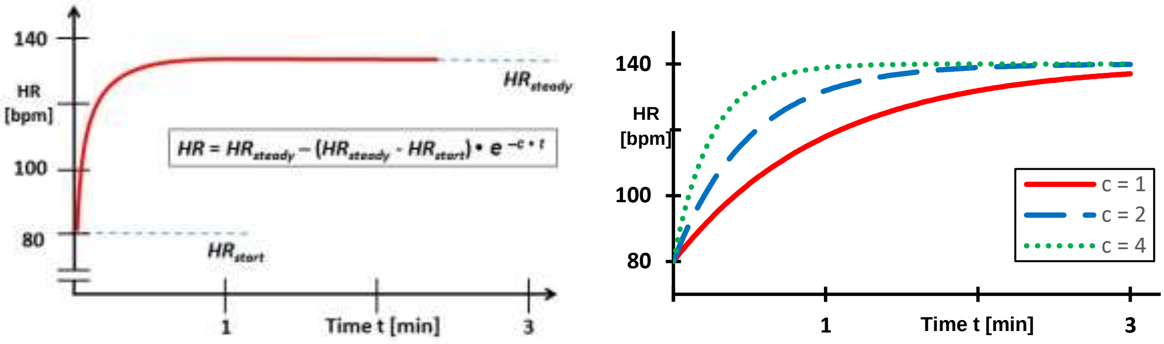

Figure 8.1 Illustration of the time course of HR according to the Bunc equation (Bunc et al., 1988). Left side: prototypical HR course illustrating the Bunc equation, right side: prototypical HR courses with different c values illustrating the influence of c on the HR course.

Hoffmann, Wiemeyer, and Hardy (2016) confirmed the feasibility of the Bunc formula for describing the individual HR response to the change of training load in the submaximal range, taking into account only selected time points.

In this paper, the Bunc formula (Bunc et al., 1988) was tested for the property to analyze and predict the individual responses to the change of load bouts. The aim of the study was to predict acute responses 'online', i.e., during training, as fast as possible without any prior knowledge of the change in the level of the training load or the individual HR responses to these changes. Therefore, HR responses to the change of load were recorded and analyzed over different time periods. Using this data, the slope of the course and the final HR (HR_{steady}) were incrementally calculated applying the Bunc formula. Subsequently, the difference of the calculated HRs from the measured HRs was calculated. The time point for a reliable and valid prediction of the HR_{steady} corresponding to the load change was estimated.

8.3. Material and Methods

The study presented here was approved by the Ethics Committee of Technical University of Darmstadt in 2016.

8.3.1. Participants and Apparatus

Four healthy and active adults (two males, two females) volunteered to participate in this study after having signed an informed consent. All participants declared that no contra indication for the training protocol existed (Washington et al., 1994). The participants' characteristics are described in Table 8.1.

All tests were performed using a cycle ergometer with a flywheel (Daum Ergometer 8008 TRS 3; Fürth, Germany). The power was controlled by the resistance at the flywheel and measured in Watts by the ergometer.

HR data was successively recorded beat by beat by a Polar V800 sport watch (Polar Electro, Kempele, Finnland). The corresponding Polar chest belt (T31) was attached to the participants prior to the training. The training protocol started after a period of 1 minute of passive sitting on the ergometer. Data recording started with the beginning of the training protocol.

Respiratory parameters were recorded during the exhaustion test and the sub test using the spiroergometry device K5 (COSMED, Rome, Italy). The mixing chamber recorded data every 10 s. First anaerobic threshold (VT_1) and second anaerobic threshold (VT_2) were automatically calculated from the respiratory parameters using the OMNIA Software (COSMED, Rome, Italy).

Table 8.1 Demographic and anthropometric description of the participants – Manuscript V.

	Participant 1 (P1)	Participant 2 (P2)	Participant 3 (P3)	Participant 4 (P4)	Total (n = 4) Mean	SD	Range
Age [years]	31	32	32	31	31.5	0.50	1
Height [m]	168	175	182	185	177.5	6.58	17
Weight [kg]	79-80	69-70	87-90	95-97	83.1	9.35	18
Sex	Female	Female	Male	Male	---	---	---
BMI [kg/m²]	28.1	23.0	26.7	27.6	26.3	2.07	6.1
Activity time per Week [h]	3.5	2	7	3	3.875	2.17	5

8.3.2. Protocol

All data was obtained during a twelve-week endurance training intervention on a bike ergometer. This duration was chosen because adaptations to training can be reliably observed after this training period (Blank, 2007). Prior to and after completion of the intervention, the participants performed an all-out exhaustion test to estimate the individual maximal HR and VO_2 max.

The protocol of the exhaustion test started with a resting period with the participants sitting still on the ergometer. After 3 min, the participants started pedaling for 2 min at 25 W, followed by 3 min at 50 W. After this warm-up period, the load at the ergometer was set to 100 W. The load was then successively increased by 50 W every 3 minutes until exhaustion (P_{max}).

Additionally, two subtests were performed in week 4 and week 8. These subtests were deployed to adapt the training intensity according to the training protocols. In the subtests, the resting and warm-up period of the exhaustion tests were repeated. Subsequently, the participants were stressed with 3 increasing load levels for three minutes each. The load was calculated to induce responses corresponding to the individual's VT_1 and VT_2 (i.e. first load (P_{1_sub}): responses below VT_1, second load (P_{2_sub}): responses between VT_1 and VT_2, third load (P_{3_sub}): responses above VT_2). At first, P_{3_sub} was calculated taking into account the load when the final exhaustion (P_{max}) and VT_2 (P_{VT2}) was achieved. The following formula was used:

– **Equation 8.2:** $\boldsymbol{P_{3\_sub} = P_{VT2} + \left(1 + \frac{P_{max} - P_{VT2}}{50\,W}\right) \cdot 10\,W}$

Subsequently, P_{1_sub} was calculated taking into account the height of the load when VT_1 was achieved (P_{VT1}). If P_{VT1} was below 200 W factor x was set to 1. If P_{VT1} was above 200 W factor x was set to 2. P_{1_sub} was calculated using the formula:

– **Equation 8.3:** $\boldsymbol{load_{1sub} = load_{VT1} - (1 + x) \cdot 10\ W}$

To ensure a constant rise of load (e.g., increase of 40 W at each level) P_{2_sub} was calculated using the formula:

– **Equation 8.4:** $\boldsymbol{P_{2\_sub} = \frac{(P_{\_1sub} + P_{3\_sub})}{2}}$

To give an example, the aerobic thresholds were recorded in the first exhaustion test at 250 W (P_{VT1}) and at 300 W (P_{VT2}). P_{max} was recorded at 350 W. Therefore, the load for the sub tests were calculated as:

- P_{3_sub} = 300 W + $(1 + \frac{350\ W - 300\ W}{50\ W}) \cdot 10$ W = 320 W
- $P_{1\_sub} = 250\ \text{W} - (1 + 2) \cdot 10$ W = 220 W
- $P_{2\_sub} = \frac{(320\ W + 220\ W)}{2}$ = 270 W.

After the 9-minute exercise period, a resting period of 5 minutes of active recovery at 25 W was applied. Subsequently, another 9-minute exercise phase and 5 min recovery phase were added, respectively.

According to the guidelines of the WHO (2010), the training volume for the training intervention was set to 25 min of intensive training three times a week. To offer a more varying and motivating training regime three different training methods were applied: the intensive continuous method (*ICM*), the extensive interval method (*EIM*) and the intensive interval method (*IIM*) (Hohmann, Lames, & Letzelter, 2002). $HR_{training}$ for the training protocols were calculated using the individual HR_{max} value obtained in the first exhaustion test. Furthermore, the load in each protocol was calculated using the HR data from the first exhaustion test and the two subtests, respectively. In the first exhaustion test, the last 30 s of every load level was therefore calculated as HR corresponding to the load levels. The load evoking the target HR was linearly interpolated from the calculated data. The same procedure was used in the subtests. However, the load was linearly extrapolated in case 95% HR_{max} exceeded HR_{steady} in the third load of the subtest. Mean load of both exercise phases were calculated as load that was expected to evoke the $HR_{training}$ for each training protocol.

The order of the training methods was permutated twice during the intervention. The previously described subtests were conducted substituting the *IIM* in week 4 and 8. All protocols were automatically applied at the ergometer. The participants were advised to keep the pedal rate (PR) constant at 80 revolutions per minutes (RPM) (Coast, Cox, & Welch, 1986).

The training protocols are displayed in Table 8.2 in detail. Figure 8.2 displays an example of the load protocol for *EIM*.

Table 8.2 Protocols for the training intervention – Manuscript V.

	Intensive Endurance Method (*ICM*)	Extensive Interval Method (*EIM*)	Intensive Interval Method (*IIM*)
Intensity	75% HR_{max}	80% HR_{max}	95%HR_{max}
Load period	25 min	3:30 min	1:00 min
Recovery Time	0 min	1:30 min	1:30 min
Repetitions	1	5	10
Warm-up	2 min at 25 W	2 min at 25 W	2 min at 25 W
Total exercise time	30 min	30 min	30 min

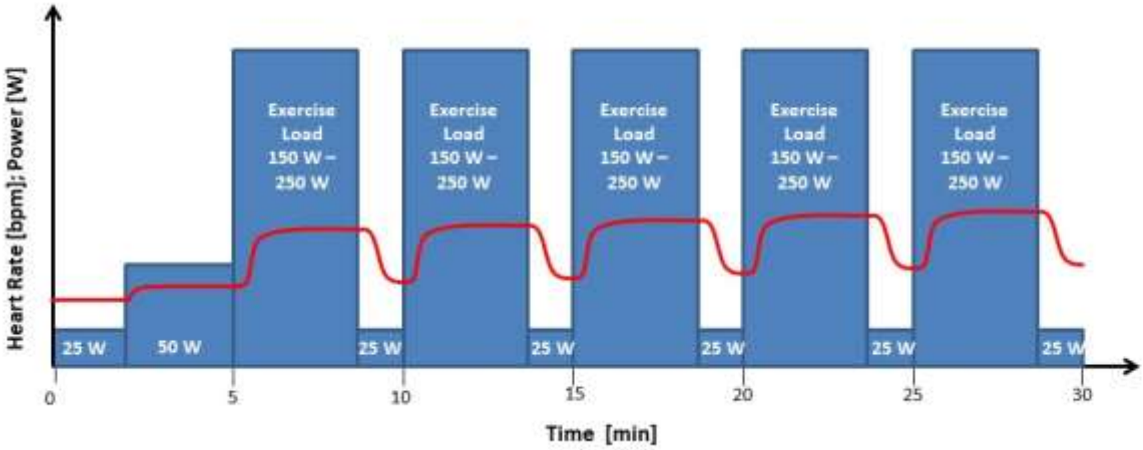

Figure 8.2 Load protocol and prototypical HR response for EIM. Training load is varying due to the training load calculated with 80% HR_{max}.

8.3.3. Data processing

The HR data for the *EIM* training protocol was analyzed. Compared to the other training protocols the HR of the participant is expected to stay in the submaximal range after an initial exponential increase. Therefore, we expected that the Bunc formula (Bunc et al, 1988) is valid for *EIM*. Additionally, the time of these load phases is expected to be sufficient for HR to reach a steady state (Kroidl, Schwarz, Lehnigk, & Fritsch, 2014).

HR data of the participants was automatically divided into exercise and recovery phases for each training protocol. The phases started with the change of the load at the ergometer. The warm-up period and the recovery phases were not part of the computations. Thus, we obtained 60 HR curves for each participant. Six curves where excluded due to measuring errors. In total, 234 data sets were processed.

The minimum value in the first 10 s of each curve was used as starting HR (HR_{start}). This was determined as the HR transition from recovering to the following exercise phase is characterized by a large variance. Therefore, miscalculation due to synchronizing errors are prevented.

8.3.4. Validity of the Bunc Formula

In order to gain first insights into the adaptation of the HR to the change of load bouts and to confirm the validity of the formula, the measured HR data was approximated using the previously described formula by Bunc et al. (1988).

Expecting the HR to reach a steady state the mean HR in the last 30 s of each exercise phase was calculated as steady state HR (HR_{steady}). According to Kamath, Fallen, and McElvie (1991) a stable HR_{steady} is reached when the HR values vary less than 5 bpm for the rest of the exercise interval. Therefore, the difference of the measured HR and HR_{steady} as well as the increase of the HR values was used for the calculation of the time point when the measured HR values reached HR_{steady} (t_{steady}). In order to prevent miscalculations, the HR was preprocessed using the moving average method with a window size of 30 s. This window size was determined by testing window sizes ranging from 10 s to 60 s. The value of 30 s is considered a reasonable compromise of precision and noise reduction. For this calculation HR_{steady} was reached, when the difference of the averaged HR and HR_{steady} was smaller than 5 bpm and the increase of the averaged HR was smaller than 5.

The beat-to-beat HR data from the onset of exercise to t_{steady} was used for calculation of parameter c. Therefore, the data was first linearized using the formula:

- **Equation 8.5:** $\boldsymbol{c \cdot t = -\ln(\frac{HR_{steady} + 1 - HR}{HR_{steady} - HR_{start}})}$

Parameter c was then estimated using the linear regression method.

As the Bunc Formula is most suitable for the description of the HR increase from the onset of exercise to HR_{steady}, this data set was used for calculation of the coefficient of determination. Additionally, the parameters HR_{start}, HR_{steady} and c were investigated. The average value of c was calculated as baseline value for the analyzed sample.

8.3.5. Calculation of HR_{steady}

The second part aimed at predicting the individual HR_{steady} online while exercising. Therefore, an incremental procedure was chosen that recalculated HR_{steady} after distinct time periods.

Due to lacking knowledge about the value c in general, the average c value for all 234 HR courses was used for calculation ($c_{average}$).

Using the Bunc formula, two defined HRs (HR_1 at time point t_1 and HR_2 at time point t_2) can be described as:

- **Equation 8.6a:** $\boldsymbol{HR_1 = HR_{steady} - (HR_{steady} - HR_{start}) \cdot e^{-c \cdot t_1}}$
- **Equation 8.6b:** $\boldsymbol{HR_2 = HR_{steady} - (HR_{steady} - HR_{start}) \cdot e^{-c \cdot t_2}}$

Using the substitution method, HR_{steady} can be calculated using the formula:

- **Equation 8.7:** $\boldsymbol{HR_{steadyCalc} = \frac{HR_2 - HR_1 + HR_{start}\,(e^{-c \cdot t_1} - e^{-c \cdot t_2})}{e^{-c \cdot t_1} - e^{-c \cdot t_2}}}$

According to Ricardo et al. (2005), the HR increase is linear and independent of the level of the change in the first 20 s after the change of load. To ensure a reliable inclusion of HR data that were depending on the load change HR_{start} and HR at 30 s after onset of exercise (HR_{30} at t_{30}) was used as first calculation period for predicting HR_{steady}. HR_{30} was calculated as mean HR over the last 5 beats to reduce the influence of HR variability.

To test the validity of the calculated HR_{steady}, an approximated HR curve including the calculated steady state HR (HR_{steady_calc}), c and HR_{start}, was calculated again. Starting with t_{50}

(time point 50 s after onset of exercise) the calculated HR (HR_{calc}) was compared to the actual HR (HR_{real}; mean value over last 5 s) at the corresponding time point. If the values differed from each other of more than 2 bmp, the value c was adapted depending the tendency of the deviation and the increase of the slope of HR. In case the increase of HR was higher than 30, value c was reduced by 0.5 if the calculated HR was higher than the real data. If the calculated HR was lower than the real HR value c was increased by 0.5, respectively. In case the increase was smaller than 30, c was reduced or increased by 0.1, respectively. This method was chosen taking into account the time course of the HR.

HR_{steady_calc} was again calculated taking into account HR_{30} representing HR_1, HR_{50} representing HR_2, HR_{start} and the adapted value c. Another approximated HR curve was calculated.

This procedure was repeated every 10 s until the end of the exercise phase.

8.3.6. Deviation of HR_{steady_calc} and HR_{steady}

To analyze the capability of the presented algorithm for predicting HR_{steady}, the deviation of HR_{steady_calc} und HR_{steady} was calculated throughout the exercise at distinct time points. Starting with t_{30}, the deviation was calculated every 10 s to analyze the prediction performance of HR_{steady} regarding efficacy and quality of prediction.

Additionally, the time point t_{5bpm} when the difference of HR_{steady_calc} and HR_{steady} was smaller than 5 bpm respectively was calculated.

The following flowchart illustrates the process (see Figure 8.3).

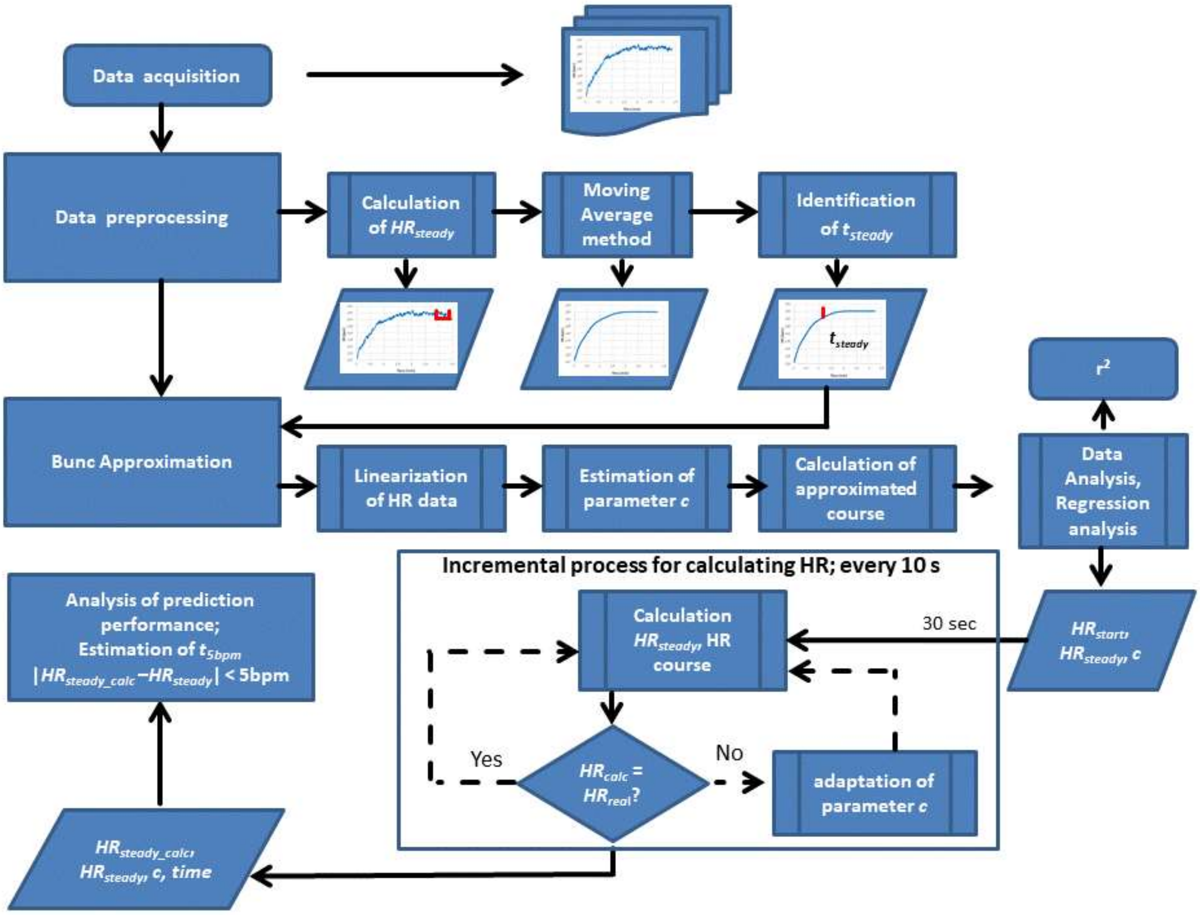

Figure 8.3 Flow Chart of the calculations. After the acquisition of HR data, all HR courses were preprocessed in three steps. HR courses were afterwards approximated using the Bunc-Formula and distinct parameters essential for calculation determined. HR_{steady} representing the steady state HR evoked by the load was predicted and the corresponding HR course modeled. After distinct time periods, the calculated HR (HR_{calc}) was compared to the measured HR (HR_{real}). In case of deviation the parameters were adapted and recalculated to fit the measured data. HR_{steady_calc} was compared to HR_{steady} throughout the modeling process. The prediction performance of the algorithm was analyzed using the obtained data. The period of calculation (t_{5bpm}) when HR_{steady} was adequately predicted was determined.

8.4. Results

As expected, a strong increase and decrease of HR depending on the load protocol can be observed in all participants. The difference from HR_{start} to HR_{steady} was higher than 20 bpm in all participants except for 2 increases of 19 bpm in week 6 in participant 2 (Overall: *Mean* = 38.8 bpm; *SD* = 8.54; *Max* = 60 bpm; *Min* = 19 bpm). An example of the HR adaptation corresponding to the induced load is illustrated in Figure 8.4.

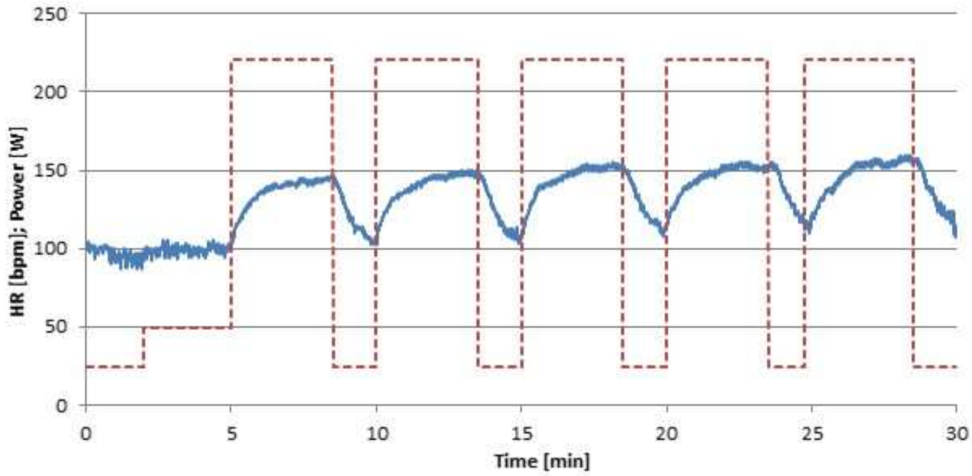

Figure 8.4 Prototypical HR course of participant 3 in week 3; the solid blue line represents the HR values calculated from the RR-intervals; the dotted red line represents the load protocol.

Statistical analysis of HR_{start} and HR_{steady} for all exercise phases is displayed in Table 8.3.

In all participants, HR_{start} increased during the training session. The highest increase was found in participant 4 (see Table 8.3). No difference of HR_{start} was observed depending on the week of the training. The differences of HR_{start} were highly significant in all participants except for participant 2 and 4 (t = .925; p = .357; see Figure 8.5).

In contrast, the differences of HR_{steady} were less pronounced in all participants. Whereas an increase of HR_{steady} during the training intervention could also be found in all participants (see Table 8.3), the difference between the participants was significant only between P1 and P3 and between P2 and P3 (Figure 8.6). Again, no overall trend of HR_{steady} depending on the week of training was observed.

Table 8.3 HR_{start} and HR_{steady} for all participants, HR_{max}: maximal heart rate achieved in an all-out exhaustion test.

	Participant 1 (P1)		***Participant 2 (P2)***		***Participant 3 (P3)***		***Participant 4 (P4)***	
	HR_{start} [bpm]	**HR_{steady} [bpm]**	**HR_{start} [bpm]**	**HR_{steady} [bpm]**	**HR_{start} [bpm]**	**HR_{steady} [bpm]**	**HR_{start} [bpm]**	**HR_{steady} [bpm]**
HR_{max}	189		185		188		193	
Mean	118.7	148.0	108.4	147.9	97.8	144.9	106.7	146.3
SD	8.9	8.8	7.8	4.6	7.9	7.5	11.2	8.0
Max	140	168	123	156	119	165	135	168
Min	97	132	82	131	81	128	86	127
Interval 1 (I_1)	116	143	103	143	91	134	92	138
Interval 5 (I_5)	122	151	111	151	103	150	116	153
Difference I_1-I_5	7	8	7	8	13	11	24	12

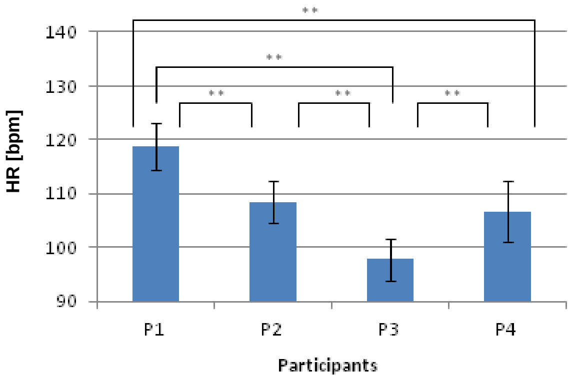

Figure 8.5 Mean HR_{start} for all participants. ** p <.01.

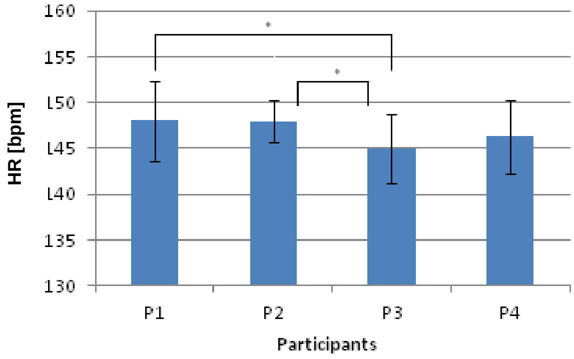

Figure 8.6 Mean HR_{steady} for all participants. * p <.05.

8.4.1. Validity of the Bunc formula

The mean coefficient of determination between the calculated Bunc formula and the measured HR data for all 234 HR data sets was r^2 = .962 (*SD* = .025; *Max* = .991, *Min* = .702.

P1: r^2 = .946 *SD* = .028; *Max* = .986, *Min* = .881;
P2: r^2 = .967 *SD* = .022; *Max* = .991, *Min* = .898;
P3: r^2 = .975 *SD* = .013; *Max* = .990, *Min* = .915;
P4: r^2 = .959 *SD* = .039; *Max* = .985, *Min* = .702).

The value *c* representing the slope of the adaptation course was varying between all participants (see Table 8.4).

Table 8.4 Value *c* for all participants.

	Participant 1	Participant 2	Participant 3	Participant 4
Mean	1.42	1.74	1.55	1.08
SD	0.506	0.452	0.224	0.186
Max	3.04	2.86	2.29	1.57
Min	0.67	0.83	1.22	0.72

To illustrate the influence of *c* on the HR course two exemplary courses with a high and low *c* value are displayed in Figure 8.7.

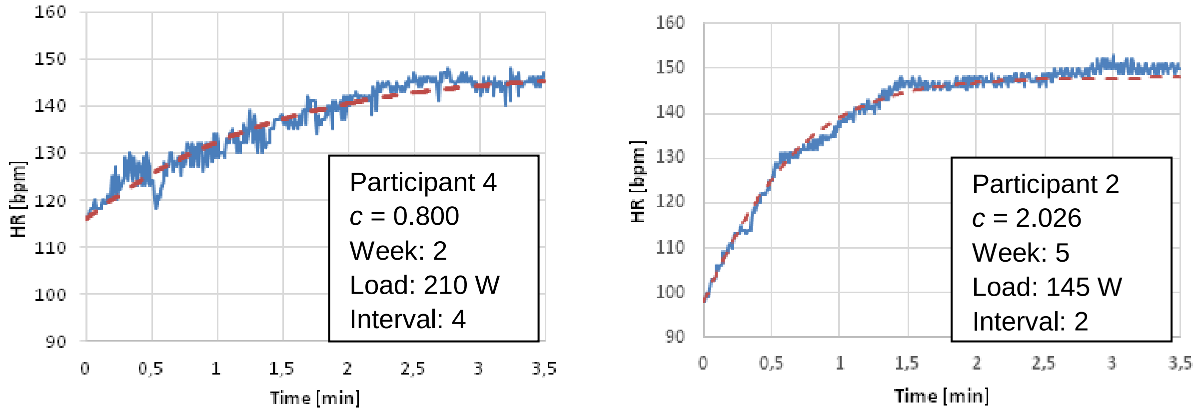

Figure 8.7 Left side: prototypical HR course of participant 4 with a low *c* value ($c = 0.800$); Right side: prototypical HR course of participant 2 with a high *c* value ($c = 2.026$). Solid blue line represents the HR values calculated using the RR-intervals; intermittent red line represents the approximated course using the Bunc formula.

Significant differences of the mean *c* value were found in all participants except for P1 and P3 (see Figure 8.8).

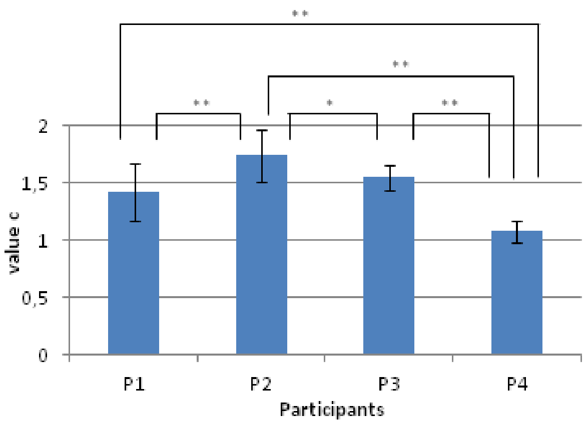

Figure 8.8 Calculated *c* (representing the slope of the HR course) for all participants. * $p < .05$, ** $p < .01$.

Additionally, *c* is varying irrespective of the week of training intervention. No overall trend was observed within twelve weeks. Value *c* was also varying irrespective of the load interval within each training session.

The difference of HR_{steady} to HR_{start} is not correlated to value *c* ($r^2 = .011$; $N = 234$; $p = .12$; see Figure 8.9).

All calculated data is displayed in Table 8.5 and Table 8.6.

Table 8.5 Value *c* depending on the week of the training intervention (week 1 to week 12) averaged for all participants.

Week	*Mean*	*SD*	*Max*	*Min*
1	1.300	0.201	1.544	1.045
2	1.325	0.234	1.687	1.073
3	1.306	0.253	1.644	1.042
4	1.585	0.425	2.193	1.129
5	1.422	0.381	1.952	1.054
6	1.565	0.278	1.900	1.221
7	1.611	0.419	2.263	1.270
8	1.573	0.299	1.935	1.208
9	1.337	0.168	1.529	1.147
10	1.312	0.268	1.653	0.986
11	1.487	0.222	1.729	1.235
12	1.499	0.353	2.043	1.181

Table 8.6 Value *c* depending on the particular training interval during the training session, averaged for all participants.

Training interval	*Mean*	*SD*	*Max*	*Min*
1	1.503	0.366	2.216	0.986
2	1.329	0.295	1.894	0.911
3	1.472	0.333	2.046	0.999
4	1.445	0.399	2.272	0.990
5	1.493	0.271	2.007	1.078

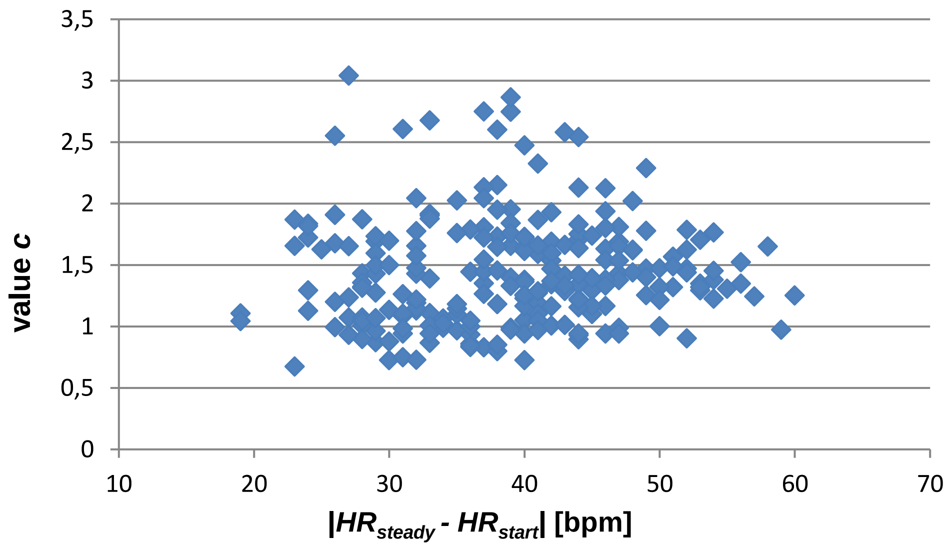

Figure 8.9 Correlation of the difference of | HR_{steady} - HR_{start}| and value c.

8.4.2. Deviation of HR_{steady_calc} to HR_{steady}

Prototypical calculation processes including the adaptation of HR_{steady_calc} throughout incremental procedure are displayed in Figure 8.10.

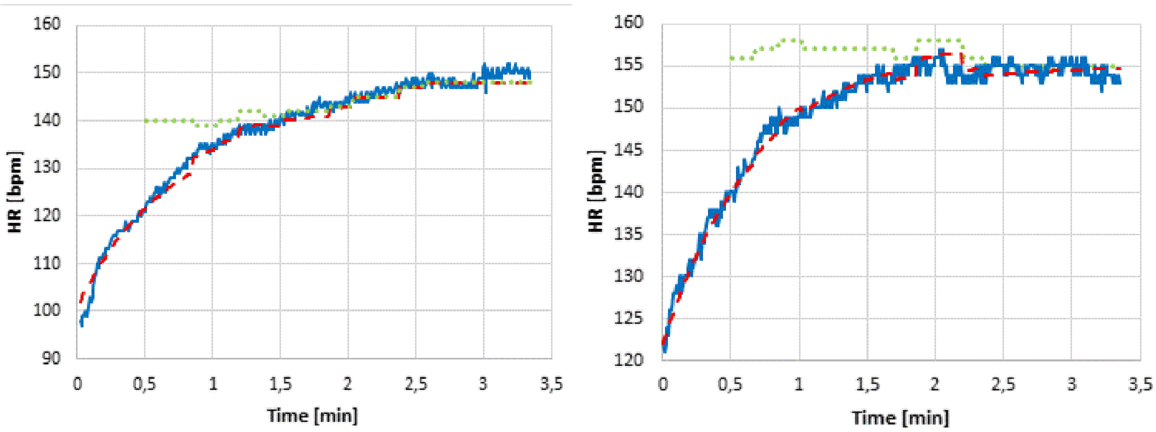

Figure 8.10 Prototypical courses of calculation of HR_{steady_calc}. Left side: Poor estimation of HR_{steady_calc} within 149 s (1.5 min) after onset of exercise. A strong underestimation can be observed (HR_{steady} = 148 bpm). Right side: good estimation of HR_{steady_calc} within 30 s (0.5 min) after onset of exercise (HR_{steady} = 154 bpm). Although HR_{steady_calc} is varying during the calculation process, the deviation of HR_{steady} and HR_{steady_calc} stays within the range of 5 bpm. Blue Solid line represents the HR values calculated using the RR-intervals. Red intermittent line represents the approximated course using the Bunc formula. Green dotted line represents HR_{steady_calc}.

The prediction quality of the algorithm was increasing throughout the calculation process. In total, all HR_{steady} values were correctly predicted after 150 s when the difference of measured to calculated HR was less than 5 bpm. Already after 30 s, HR_{steady} was correctly predicted in 95 out of the 234 courses. The amount of correct recognition increased to 161 (out of 234 courses; 69%) after 60 s and to 186 (out of 234 courses; 80%) after 90 s, respectively.

However, the correct recognition was varying between the participants. Already after 60 sec, the correct HR_{steady} was predicted in 48 out of 60 courses (80%) in participant 1, in 47 out of 60 courses (78%) in participant 2 and in 47 out of 55 courses (85%) in participant 3. After 90 s, the deviation of HR_{steady} and HR_{steady_calc} was smaller than 5 bpm in 53 out of 60 courses (88%) in participant 1, in 54 out of 60 courses (91%) in participant 2 and in 54 out of 55 courses (98%) in participant 3. In contrast, the amount of correct recognition was only 32 % (19 out of 59 courses) and 42 % (25 out of 59 courses) in participant 4 after 60 s and 90 s, respectively.

All data of correct prediction of HR_{steady} when the difference of measured to calculated HR was less than 5 bpm after distinct time periods and cumulative recognition of HR_{steady_calc} for all participants are illustrated in Figure 8.11.

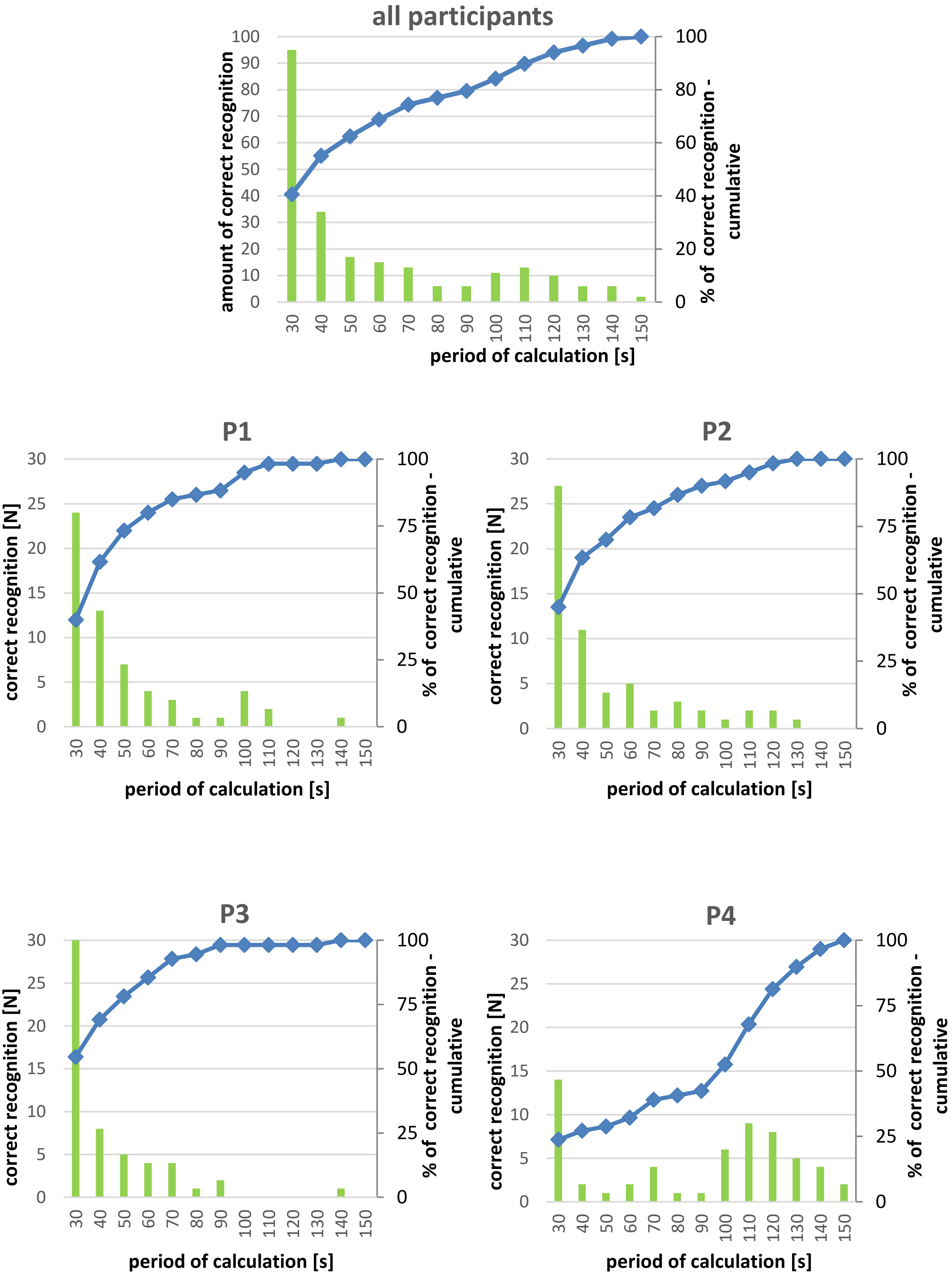

Figure 8.11 Amount of correct calculations of HR_{steady} after distinct periods of calculation illustrated for all participants and each participant individually; dark blue: amount of cumulative correct calculations in %; light green: amount of correct calculation itemized for each time point. For example, P1 showed 24 correct estimations of HR_{steady} when HR data from t0 to t30 were included (green bars); additional 13 correct calculations were achieved when HR data from t0 to t40 were included. Cumulative detection rate increased from 40 to 61.6 per cent (blue line).

Considering the mean deviation of HR_{steady_calc} and HR_{steady} after the given calculation periods for all participants, a decrease in absolute deviation and corresponding standard deviation can be observed. All data is displayed in Table 8.7.

Table 8.7. Mean deviation of HR_{steady} and HR_{steady_calc} for all participants

Period of calculation [s]	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**130**	**140**	**150**
***Mean* [bpm]**	6.14	6.11	5.29	4.80	4.65	4.22	4.19	3.67	3.27	2.78	2.42	2.25	1.94
SD	5.17	5.15	4.60	4.08	3.99	3.59	3.60	3.03	2.88	2.46	2.15	1.91	1.69

In general, the final HR was predicted after 57.8 s (*SD* = 34.77, *Max* = 150 s, *Min* = 30 s). The poorest calculation of HR_{steady_calc} was found in participant 4. Whereas in the other participants HR_{steady_calc} was correctly calculated in average after 48.1 s, the calculation for participant 4 took 86.8 s (P1: *Mean* = 49.5 s, *SD* = 26.13; P2: *Mean* = 50.0 s, *SD* = 27.62; P3: *Mean* = 44.8 s; *SD* = 24.39; P4: *Mean* = 86.8 s; *SD* = 41.19).

8.5. Discussion

In this study, the monoexponential formula developed by Bunc et al. (1988) was tested for the validity to analyze and predict the individual responses to the change of load bouts. The HR data clearly shows that even though a high variation in HR_{start} can be observed, the algorithm performed fast in most HR courses and provided sufficient results for HR_{steady} without knowing the level of the change in load or the individual HR responses to these changes.

Considering the amount of correct recognitions and the mean deviation of HR_{steady_calc} and HR_{steady} for all participants, the algorithm performs reasonable in most participants after a calculation time of 60 s. However, the prediction quality after a calculation period of 90 s is with almost 80% of correct recognition and a mean deviation of 4.19 bpm (*SD* = 3.60) increased.

Analysis revealed that the c value is independent of the week of the training intervention, the load intervals in each training session, or the difference of HR_{start} and HR_{steady}. Rather, *c* seems to be very individual due to significant differences among the participants. Further research is required to answer the question, if an influence of long-term training can be verified or if further influences on c can be detected.

Additionally, the signal processing of the HR data calculated from the RR intervals is challenging. As the heart rate variability is highly modulated by internal influencing factors (i.e. venous return flow, breathing of the participant), it is very challenging to take into account all possible influencing factors on the HR. Therefore, the preprocessing of the signal needs to be improved. One possibility might be the averaging of the HR data. However, determining the optimal window size is still challenging to balance precision and noise reduction (i.e. HR_{start}, HR_{max}). Additionally, the specific analysis of distinct parameters might improve the prediction. For example, one of these parameters is the time point when the HR course changes from linear to exponential increase. As proposed by Engelen, Porszas, Riley, Wasserman, Maehara, and Barstow (2013) a small plateau of HR can be observed. Plateaus were found throughout the HR course due to variances (81 out of 234 courses – 34%). In these cases, the Bunc algorithm might lead to a misinterpretation of a transiently steady HR as HR_{steady}. Additionally, the incremental calculation might incorrectly adapt the value *c*.

As the baseline value for *c* was calculated over all participants, the algorithm performed best when the value *c* for the analyzed data set matched $c_{average}$ = 1.5 calculated prior to the analyses. Additionally, a fast recognition was observed with *c* values higher than $c_{average}$. (1.5 < c). The poorest results were achieved when the *c* value calculated for a particular phase was less than 0.8.

This was especially apparent in participant 4. Due to the delayed correct calculation, HR_{steady} was often underestimated. As the algorithm was developed to fit the HR_{steady_calc} to the data especially when a strong increase can be observed, the small *c* might lead to only small adaptations of the value *c*. This might provoke a delay as HR_{steady_calc} is recalculated only every 10 s. Therefore, the parameters for the adaptation of the value *c* during the calculation process require further refinement. Especially, deflection points when the increase of the HR flattens should be integrated in the calculation. Including more than the currently used two time points might lead to a faster and more reliable recognition. Additionally, the baseline for value *c* requires refinement und needs to be estimated in a wider group.

Further analyzing the HR data of participant 4 revealed that the HR might not reach a stable steady state but keeps increasing beyond the submaximal range. Therefore, future research should address the question if the formula is feasible for predicting HR that exceeds the submaximal range. Additionally, future investigations should also examine other training protocols (i.e. intensive or extensive training methods) or the HR course during regeneration phases.

Furthermore, the validity of predicting HR_{steady_calc} should be investigated using and comparing further formulas or procedures (i.e. Le et al. 2008; Cheng et al., 2008) that were described earlier. This might give insight if more parameters are essential for a more valid and faster prediction.

Additionally, further research needs to address the question how the load has to be adapted in case the load is predicted to be insufficient or overstraining for optimal training adaptation.

8.6. Conclusion

The monoexponential formula from Bunc has the potential to be used as a method for predicting individual strain without knowledge of the change in level of load. However, the prediction algorithm requires further refinement to improve the quality and the speed of the prediction. Especially, HR courses with a slow increase were not predicted sufficiently. More parameters of the HR reaction should be included in the calculation, i.e. distinct deflection points or plateaus of the HR course. Furthermore, the signal processing of the HR needs to be improved to prevent miscalculations due to variations of the HRs.

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9. Thesis Conclusion

In this chapter, the main insights and implications of the presented articles are discussed and integrated into a larger picture. Furthermore, limitations of the work are discussed and an outlook for further research is provided.

The thesis "Individualized load control in Exergames" aimed at the implementation and improvement of strain control within Exergames for aerobic endurance training controlled by a bike ergometer. Therefore, the knowledge about individual HR responses to the change of load bouts within a physical training process was extended. Parameters influencing the individual HR responses were analyzed and essential parameters for a valid HR prediction identified. Different approaches for controlling and predicting the individual HR response within Exergames were developed and analyzed.

9.1. Extension of knowledge about HR responses within a physical training

The physiological background regarding training and individual responses to training was presented. Studies presented in this thesis show that acute HR responses to the change of load during a physical training were highly variable. Analyzing the HR data revealed that responses can vary not only between different individuals but also within the same individual stressed with identical load. This effect is confirmed by the deviation from the pre-calculated $HR_{training}$ that is expected to be evoked by a distinct load and the actual HR responses measured during training.

The development and use of individual HR response patterns for the control or prediction of individual HR responses requires further attention. However, the predictive power for single training sessions is limited due to the high variability of measured HR responses.

Summarizing all results, it is not possible to evoke a defined HR response using solely a pre-calculated load. Further factors influencing the individual responses and the course of HR response must be considered accordingly.

9.2. Identification of relevant influencing factors that are essential for an improvement of HR prediction

Regarding literature, there are several possible factors that influence HR responses to the change of load. The influence of single parameters has already been verified in existing empirical studies. However, studies performed in this thesis clearly show, that single parameters do not provide sufficient information for precise modeling and prediction. Furthermore, the results confirm, that a prediction of individual acute HR responses is not valid using exclusively rather constant parameters such as age, gender, or body weight as predictor variables. This is important as it contradicts the results of basic literature focusing on HR responses (e.g., Bunc et al., 1988; Valentini & Parati, 2009).

Furthermore, the integration of short-term and varying influencing factors is essential for reliable and valid prediction of HR responses. One important short-term influencing factor was the number of performed intervals during a training session. Thus, a significant influence of Cardiac Drift in short term training sessions lasting up to 30 min (Wingo, LaFrenz, Ganio, Edwars, & Cureton, 2005) was found in the presented studies. In addition, mood, physical health, nutrition and time of day were identified as influencing factors. It should be noted, that the contribution of these influencing factors was varying individually. On the one hand, not all of these parameters affect the HR course consistently in different individuals. On the other hand, the influence of all assessed factors on particular HR parameters was verified for individual participants. Based on the obtained results, particularly HR_{start} is expected to be a factor essential for prediction. For a valid and accurate integration of strain control in Exergames, the described parameters have to be considered, processed and integrated correspondingly.

9.3. Development and analysis of different approaches for control and prediction of HR.

In total, four different approaches for control and prediction of individual HR responses were presented in this thesis:

The first approach aimed at extrapolating a load that is expected to evoke a desired training HR. The calculation was based on individual HR responses to defined load bouts. The second algorithm adjusted the load corresponding to measured responses to keep HR inside a defined HR zone. The third approach aimed at the prediction of individual HR by analyzing current HR responses. Thus, the monoexponential Bunc formula was investigated taking into account only currently measured HR values. After validation of this formula, an incremental procedure using current HR data was developed and validated to predict the individual steady state HR to the change of load bouts online during training. Furthermore, individual short-term influencing factors were analyzed for their capability to predict individual, submaximal HR responses.

Although all of these approaches seem to be promising, none of them was completely accurate for each subject:

The first algorithm caused varying and overshooting HR responses due to insufficient determination of the participants and possible short-term influencing factors. The second part of this algorithm aimed at guiding the individual HR into a defined HR training zone ($HR_{trainingScope}$). Although the mean HR was within the expected training range in all participants, the individual HR responses transiently increased this training range. Due to the adjustment of load only at defined time points, HR responses within this time points were ignored. Furthermore, this algorithm only adjusted the load in case the HR response increased or fell below the training zone. A prediction of the HR course allowing an early load adjustment was not implemented.

The incremental prediction of HR was feasible in three of four participants. However, one participant showed a very slow HR course. Therefore, the algorithm predicted the steady state HR on average only shortly before the end of exercise.

The analysis of short-term influencing factors is very promising. However, the effect size was low for factors influencing parameter c.

Additionally, every approach revealed weaknesses that made adjustments necessary during the performed studies. For example, the time for calculating mean HR responses was reduced in the first algorithm or the classification of the participants was optimized.

Although there are many further approaches and algorithms available in literature (i.e. Ludwig, Sundaram, Füller, Asteroth, & Prassler, 2015) none of them fully and equally reflect the physical adjustment processes to the change of load of a human body so far. Most of these approaches are developed and optimized to perform best with the available data sets. Furthermore, due to the high amount of possible influencing factors and due to the unpredictable variation of HRV, modeling of HR measurements can never be completely precise. The ultra-short-term modulation of HR therefore acts as internal source of error for HR modeling and prediction. It is essential to find a balance between precision of modeling real HR data and precision of prediction by averaging the data.

Regarding the findings of the thesis, an online prediction and control of individual strain based on current HR responses during training seems to be most feasible. However, varying influencing factors essentially have to be integrated to improve the predictive quality. Due to the immediate and computerized analysis of these responses, an objective and fast strain control can be integrated in Exergames.

9.4. Limitations of own work

Although new insights and reasonable approaches for controlling and predicting HR responses in Exergames are presented, this thesis has its limitations.

The primary limitations of this work are the small sample sizes of the studies. Due to the lack of knowledge addressing the individuality of HR responses to the change of load no fixed sample sizes were calculated a priori to ensure incremental methodology. Furthermore, particularly the conduction and analysis of the long-term training intervention required a high effort. Therefore, this thesis mainly focused on individual analyses. Particularly in Manuscript IV, the post-hoc calculated statistical powers using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) are accordingly low (α = .05; minimum calculated power: 1 – β = .085; maximum calculated power: 1 – β = .338). For this reason, the knowledge gained is still not complete and comprehensive. Although the high individuality is already apparent with few participants, the current findings need to be expanded and verified in larger samples or objective data sets. In particular, the occurrence and characteristics of short-term influencing factors should be investigated. However, the required sample size to obtain high power values (α = .05; 1 – β = .90) is highly varying depending on the analyzed parameter and included influencing factors. Thus, the minimum sample size analyzing the influencing factors (HR_{start} included) on HR_{steady} is 13, whereas the minimum sample size analyzing the influencing factors on the HR course (c, HR_{start} not included) rises up to 245.

Furthermore, only the HR responses of the Extensive Interval Method were analyzed in this thesis. Particularly, analyzing the HR responses during the Intensive Continuous Method might improve the knowledge about the occurrence and disposition of the particularity Cardiac Drift (see chapter 2). An unpublished study performed in our lab demonstrated that Cardiac Drift is a crucial factor identifying individually optimal load in HR-controlled aerobic endurance training. In this study, load was adjusted to keep the HR in a predefined HR range (ALC – see Manuscript I and Manuscript II). Cardiac Drift was found in each of the 104 training sessions lasting 30 minutes. However, the occurrence and the characteristics were varying individually. In contrast to the expectations and the literature (Wingo et al., 1993), the amount of load reductions to maintain the individual HR within the HR range was neither increasing throughout the training nor increased in the last part of the training session. In contrast to the expectations, even a high amount of load increases were found in all participants. These load increases occurred more frequently in the last five minutes of the 30 minutes of training sessions. This emphasizes the importance of further research addressing the individual disposition of Cardiac Drift in short term training sessions.

Furthermore, analyzing HR responses during the Intensive Interval Method or further training methods (presented in chapter 2.4) might increase the knowledge about responses exceeding the submaximal range. Additionally, the course of the HR recovery was not included in the analysis (Lamberts, Swart, Capostagno, Noakes, & Lambert, 2010).

The individual training intensity for the Extensive Interval Protocol was derived using the individual O_2 uptake, CO_2 output, and HR responses. In training science literature, further parameters characterizing individual performance thresholds are available. A very common parameter is lactate. Properly performed, the obtained individual lactate performance curve also provides valuable information about the metabolic processes of the human body during training. The integration of this information might improve the determination of training intensity. However, this parameter also depends on variety of influencing factors (e.g., amount of muscle fibre types, nutrition, time under load, pre-fatigue and overtraining; Holfelder & Bubeck, 2012; Heck & Beneke, 2008). The performance of the tests and the subsequent determination of lactate should therefore be carried out with caution to obtain valid results.

A precise HR prediction proved to be difficult due to the lack of available information regarding the training person, especially in the desired context of health sports. This particularly accounts for the acquisition of short-term influencing factors. Literature shows, that e.g., the ambient temperature and climate conditions, the associated perspiration rate and concurring dehydration have a strong influence on HR and SV in particular during a training session (Sawka & Coyle, 1999, Coyle& Gonzalez-Alonso). Due to a lack of air conditioning, it was not possible to keep the temperature and humidity in the laboratory constant throughout the training interventions. Occasionally, these factors were varying even during a single training session. Weather-sensitive participants occasionally felt uncomfortable due to fluctuating air pressure.

In this thesis, mood was assessed using the SBS (Hackfort & Schlattmann, 1995). Since mood was revealed as strong influencing factor on HR responses, these parameters also need to be further analyzed. In general, SBS assesses mood in eight dimensions with only one item per dimension. Although this questionnaire has proven to be time efficient, the validity of the results requires critical reflection. Factor analysis calculated for all participants revealed medium inter-correlation between subscales for the positive (Pearson r: Min = .43, Max = .74) and negative (Pearson r: Min = .46, Max = .74) items. All correlation were highly significant ($p < .01$). Therefore, a clear differentiation of the items corresponding to Hackfort and Schlattmann (1995) can not be confirmed. However, summarizing the items into positive and negative mood was reasonable, since all correlations between the positive and negative items were negative. In future research, the use of different questionnaires might be considered (e.g., "Profile of Mood States" POMS; McNair, Lorr, & Droppleman, 1971). In contrast to SBS, POMS measures only six dimensions of mood using 65 questions. The internal consistency of POMS is reported to range from .84 to .95 (McNair, Lorr, & Droppleman, 1971). Since 1971, POMS was continuously validated and revised. Furthermore, a variety of versions corresponding to analyzed target groups or required time is available (e.g., POMS-Y for youth with 60 items, POMS Short with 35 items; Lin, Hsiao, & Wang, 2014). The assessment of psychological profiles of the participants might also be useful in order to better classify and interpret the obtained values. Furthermore, different assessment tools might be useful. Bachmann et al. (2015) for example, developed a smartphone application that additionally recognizes the mood using smartphone-based wearable sensors.

Another very important factor that was only briefly addressed is the influence of the particular Exergames on HR responses. Especially, in-game variables and the parameter used for game control have to be considered and further analyzed. Literature also proved that motivational game elements (causing e.g., arousal or happiness) influence the individual HR responses (Ellermeier, Göbel, & Wiemeyer, 2013). These parameters need to be further analyzed regarding their short-term influence on HR responses but also regarding their influence on mood during training. Additionally, further influencing factors not yet assessed in the studies should be included in analysis. Regarding to literature, for example, an influence of the (preferred) pedal rate (Löllgen, Graham, & Sjogaard, 1980; Hansen, Andersen, Nielsen, & Sjøgaard, 2002), ambient temperature and humidity, or the menstrual cycle on individual strain parameters such as HR or VO_2 was demonstrated.

However, the inclusion of as many influencing factors as possible might improve the prediction quality but decreases the usability of the Exergame at the same time. Therefore, another very important question is what information or data is required to establish a reasonable compromise between analyzed data and prediction quality.

In this thesis, modelling and predicting individual strain was performed using the monoexponential formula postulated by Bunc et al. (1988). Although this formula shows high validiy in the analyzed samples, further research should investigate and compare formulas or procedures for controlling, modelling and predicting individual strain (see chapter 6). These approaches must be analyzed for their feasibility and reliability since no laboratory conditions, expensive devices assessing further strain parameters or big data sets for learning are available in the intended context. Another possibility is the use of machine learning algorithms and specific neuronal networks for prediction. According to Ludwig et al. (2015), only simple feedforward neuronal networks were used in the past. *Recurrent Neuronal Networks* or *Long Short-term Memory Neuronal Networks* might be used to identify time-coded information in the data or capture individual dependencies (Lipton, Kale, Elkan, & Wetzel, 2015). Furthermore, approaches from control engineering might be used for HR control. Studies investigated the feasibility of a PD- or PID-controller with HR as manipulated variable and load as control variable. Regarding to Wagner, Kirchner, Kollenbaum and Dahme (1993) this controller can be used for systems without mathematical description due to varying factors that cannot be determined beforehand. First evidence suggests that the controller might be an effective and efficient way to evoke HR_{target}. However, first unpublished studies performed in our lab show that the controlling parameters also have to be adjusted individually. Additionally, further research is needed integrating varying influencing factors in this controller as well.

One of the key challenges for future research is the implementation of the developed algorithms in Exergames integrating the described limitations. Thus, Exergames can be used as effective and efficient training tools.

9.5. Outlook

In this chapter, the implications for further research integrating a broader perspective are presented.

In order to integrate strain control into Exergames, it is essential to make important additional information (e.g., variable short-term influencing factors) available inside the Exergame. Either input fields need to be implemented in Exergames or the information has to be assessed using corresponding sensors. Due to the technological process, the development of smaller and more valid sensors increases rapidly. For example, sensors have been developed that are designed to reliably determine the amount and composition of sweat produced during exercise (Gao et al., 2016, Bandodkar, et al., 2014). However, reliability and usability of these sensors are important issues that also require investigation.

Furthermore, an aspect only briefly addressed in this thesis was the game experience. A positive game experience is a crucial component, since Exergames intend to provide an entertaining and motivating computer or video game that is additionally accomplishing a serious goal. As stated before, an individual optimal task difficulty increases the motivation and adherence to the game. The use of Exergames as reasonable and engaging training tools requires the optimal fit between training content, game design and used technologies (Caserman et al., 2020).

Future research should also address the question how the findings of this thesis can be transferred into the long-term training process. This includes the question of how to define the individually optimal training HR. So far, training intensities were determined by literature review. However, findings in this thesis suggest that up to date literature on individual HR responses is insufficiently available. This is exemplarily evident by the inadequate reflection of the variety of individual HR responses. There is a lack of meaningful studies on whether athletes performing different sports (e.g., weight training, endurance sports) show varying HR profiles. Due to different energy supply of the muscles and working systems or varying muscular recruitment they correspondingly might require varying HR zones for optimal aerobic endurance training. A promising approach might be the additional analysis of heart rate variability (Hottenrott, Hoos, & Esperer, 2006).

In this context, a term important for training but not fully clarified is “Steady State”. Although steady state HR can be defined as “HR varying less than 5 bpm throughout the exercise period” (Kamath, Fallen, & Mckelvie; 1991), this definition remains unclear without a distinct time frame for measuring. Additionally, different organ systems of the human body might reach a steady state at different load conditions. Although a steady state was confirmed in all data sets of EIM, the measured time frame was probably too short for a valid determination. Thus, HR was still increasing but less than 5 bpm within the measured time frame. Further problems not yet solved are the particularities of cardiac drift, prestart-HR, and decrease of HR into steady state. Neither the physiological basics nor appearance of this particularities are yet finally clarified.

Due to the individuality of responses, the results of this thesis are not limited to the specific field of HR responses in bike ergometer controlled Exergames. It might also be transferred to further Exergames integrating physical activity for aerobic endurance training (e.g., training on cross trainer, treadmill or dancing) or to parameters of the human body reflecting individual strain (e.g., VO_2, VCO_2). Furthermore, the results might also be expanded to other applications controlling individual strain (e.g., human movement assistance in prosthetics).

9.6. References

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